CLASSIFICATION OF FOREST VEGETATION IN NORTH-CENTRAL MINNESOTA USING LANDSAT MULTISPECTRAL SCANNER AND THEMATIC MAPPER DATA

A THESIS

SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL

OF THE UNIVERSITY OF MINNESOTA

By

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

March 1987

DEGREE GRANTED
JUL 87

FOR, THS

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ACKNOWLEDGEMENTS

A number of people generously helped and influenced me on this project and I would like to take this opportunity to thank them. First, I would like to thank my major professor, Dr. Marvin E. Bauer for his inspiration, time, support, and enthusiasm for my research. Dr. Merle P. Meyer, who gave me my start in Forest Resources, taught me to be a professional and deepened my appreciation for natural resource management. I would also like to thank my other committee members, Dr. Alan R. Ek, Dr. Margaret B. Davis, and Dr. David F. Grigal. I admire their capabilities, both in teaching and research, and they have greatly influenced my education.

Doug Meisner and Bill Johnson, research fellows with the Remote Sensing Lab, what can I say? You both taught me much of the technical necessities to carry out my research, were always willing to answer questions, and really helped me complete this project. You are also special friends.

This project was supported by the University of Minnesota's Agricultural Experiment Station project numbers 42-37 and 42-38. I would also like to thank the Department of Forest Resources for additional support through a teaching assistantship.

I would also like to thank the School of Forestry, Northern

Arizona University in Flagstaff for the time and support they provided over the past few months while I completed my dissertation.

Last, but certainly not least, I owe a lot to my friends and family. I wish that I could personally thank each of my fellow graduate students and friends who made graduate school so enjoyable. I hope that I will be able to do so over the years. To my family in Virginia, thank you for your support and strength while I pursued this goal. Although it was across many miles, I felt you with me every step of the way!

ABSTRACT

Computer classifications of Landsat-5 Thematic Mapper (TM) and Multispectral Scanner (MSS) data were evaluated to determine how forest and sensor characteristics affect the classification accuracy of forest cover types in Itasca State Park, Minnesota. The initial portion of the research involved a statistical comparison of two coincidental data sets (May 18, 1984) from the TM and MSS sensors. The second portion of the study involved determining which TM combination of four dates and seven spectral bands of TM data would provide the highest classification accuracies. The final portion of the study involved the evaluation of multitemporal TM data, including a spectral-temporal profile model, for forest type classification.

All analyses were performed on a microcomputer-based image processing and geographic information system. To evaluate classification performance the Landsat classification maps were comapred on a pixel by pixel basis with a digitized reference map of the Park. Subsequently, boundary filters of 2x2, 3x3 and 4x4 pixels were applied to the reference data to eliminate the effects of mixed, boundary pixels prior to comparison with classification maps. Initially, 14 Level III vegetation classes were used in the analysis, then aggregated to ten, seven, and four classes, respectively. Overall classification results were compared for

statistically significant differences using discrete multivariate statistics. Classification accuracies ranged from 29 to 87%, depending upon the sensor, method, number of classes, and filter used.

Results indicate: (1) the increased spectral/radiometric resolution of the TM data result in 15-20% increase in classification accuracy over MSS data; (2) most of the classification error (up to 18%) occurs with mixed boundary pixels; (3) classification accuracies for May and July Landsat data acquisition dates were higher than for February and September; (4) the best spectral band combination was dependant on the date used, although one band from the visible, near infrared, and middle infrared is recommended; and finally, (5) multitemporal data did not significantly increase classification accuracies over either of the best two single dates.

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1. INTRODUCTION

1.1. General

Since the launch of the first Landsat satellite in 1972, there have been numerous studies that have addressed the potential applicability of these systems for forest resource assessment. The majority of results have demonstrated that the recognition and description of forest characteristics is difficult using satellite-acquired Multispectral Scanner (MSS) data, and resulting classification accuracies have been generally low. The Thematic Mapper (TM) is a relatively new sensor (1984 launch) that has finer spatial, spectral, and radiometric resolution than does the MSS. Many investigators, therefore, look to the TM with great interest as a possible solution to past disappointments.

Classification accuracies of forest features are greatly dependent on the heterogeneity and condition of the vegetation, spatial and spectral resolution of the data, level of detail desired, and the processing technique used (Latty and Hoffer, 1981). In the past, researchers have tended to dwell on one aspect of the classification problem, and neglected to statistically evaluate reasons for low accuracies. Only after we study the variables contributing to low accuracies can we determine if satellite data are truly useful for forest classification and inventory purposes, or if limitations can be solved.

The focus of this study has been to determine how various forest and satellite sensor characteristics affect the classification accuracies of forest cover types in north-central Minnesota. Major areas of emphasis were: (1) to identify and quantify through statistical analysis whether the limitations in classification accuracy are due to spectral, spatial or temporal (or a combination of) factors, and (2) to evaluate several new techniques that have proven successful for classifying agronomic crops, yet have not been applied to forest types.

An intensive rather than extensive study was conducted which controlled the choice of study area, data collection, and hardware/software used for data storage and analysis. The study area chosen was Itasca State Park (12,950 hectares or 32,000 acres) in north central Minnesota. All of the data processing and analysis were conducted on an IBM PC/AT microcomputer using a commercially available image processing and geographic information system called Earth Resources Data Analysis System (ERDAS).

1.2. Objectives and Hypotheses

The investigation has been a three-part study to determine how various forest and satellite sensor characteristics affect the classification accuracies of forest cover types in north-central Minnesota.

Part one deals primarily with a statistical comparison of the classification results of two coincidental data sets from two Landsat satellite sensors - the Multispectral Scanner (MSS) and the Thematic Mapper (TM). Since the TM is relatively new (1984 launch) there have been few results to date that verify that higher classification accuracies will be obtained on forested sites. The hypothesis was that the finer spatial resolution of the TM might in fact cause more confusion than does the MSS in forest cover type classification since it is able to resolve discontinuities in the forest canopy that the coarser resolution of the MSS data "smooths" out. However, I hypothesized that the overall classification performance of TM might be superior to that of MSS, due to the greater spectral and radiometric resolution. To test this hypothesis the TM data were degraded to the same spatial resolution as the MSS data, and classification results of various spatial and spectral combinations were compared to the same reference data. Discrete multivariate analysis techniques were used to compare results for statistical significance.

The second portion of the study concentrated solely on TM data. The importance of various spectral bands was analyzed for single and multiple dates. Four dates (over Itasca State Park) of the TM data were acquired within the same year (1985) to investigate how phenological changes, and therefore spectral reflectance responses, affect classification results. Dates were chosen that represent unique, annual, phenological events: dormancy (mid-February), leafout (mid-May), peak production (early July), and leaf coloration (late September). Certain spectral band combinations were investigated for each phenological event, separately and in combination, to determine which spectral bands yield the most information. The hypothesis was that one date, or a combination of dates, would yield a unique spectral signature for a particular cover type that would lead ultimately to better classification. May and September dates should yield higher overall classification accuracies for individual forest types because of distinct spectral signatures that are inherent in these seasonal extremes. February should have the highest classification accuracy for separating more general classes such as conifer, deciduous, and others. The July date should result in the lowest overall classification accuracy because the active growth in all vegetation may have a tendency to average the spectral responses (i.e., everything looks like green vegetation). From a practical viewpoint, this portion of the study was designed to contribute to a wiser choice of dates and band combinations for use in operational inventories.

The final portion of the study focused on the usefulness of some techniques that were recently developed for remote sensing studies in agriculture. The first technique involved applying linear transformations of the Landsat data in a manner that relates the biophysical characteristics on the ground to radiance values captured on the satellite image. This transformation is referred to as the Greenness-Brightness transformation (Kauth and Thomas, 1976), where greenness is highly correlated with the amount and kind of green vegetation in the scene. A second and lesser investigated technique is the temporal profile model (Badhwar et al., 1982). This model uses the Greenness-Brightness transformation, specifically the greenness coefficients, and models these values for specific plant species over time. The assumptions uderlying this approach is that species can be more easily separated over a time internal than as one point in time. Although these approaches have improved crop identification and are considered to be significant advancements for agricultural remote sensing, few studies have investigated their possibilities for forest applications. For this study, the spectral data from five dates (February, May, July, August, September 1985) of TM sensor data were transformed and modeled using this temporal profile approach. These new techniques should yield higher classification accuracies for forest cover types than does the traditional single-date classification procedures.

2. LITERATURE REVIEW

2.1. Introduction

Foresters and ecologists have long been interested in the identification, description, and classification of forest cover types. Data on the aerial extent, present condition, and change of these cover types are often needed for inventory, management and research. As a result, practical procedures that yield timely, accurate, forest cover type information are desired. Methodologies involving the use of remote sensing techniques have been investigated to determine their potential as tools to complement conventional classification and mapping efforts. Aerial photography is a well-established tool for forest cover type classification and mapping (Heller and Ulliman, 1983). The use of satellite imagery (e.g., Landsat) and computer-aided analysis for such studies is a relatively recent development. Satellite data offer certain advantages for land classification and mapping efforts, such as: (1) a synoptic view is obtained for large areas; (2) the multitemporal views of the scenes of interest are available for analysis; (3) spectral, spatial and temporal features of the landscape can be quantified; (4) satellite scanners can sense wavelengths that film cannot; and finally, (5) the data are computer compatible which is advantageous for rapid analysis and update, and for use in geographic information systems.

There are many parameters which are fundamental to the extraction of information on a landsat satellite scene. A few of the parameters which are pertinent to this study include: (1) spectral resolution,

(2) spatial resolution, (3) temporal dimension, and (4) information classes desired. The interrelationships among the factors are also likely to be significant.

The nature of each of these parameters must be understood in order to extract meaningful information from remotely sensed imagery. It is important to note that the two satellite sensors examined in this study (MSS and TM) differ in these parameters (Table 1), and therefore are expected to differ in the classification accuracies that result.

2.2. Comparison of MSS and TM Characteristics

Today, there are two major Landsat sensors: the Multispectral Scanner (MSS) and the more recent Thematic Mapper (TM). These sensors differ in spatial, spectral, and radiometric characteristics. Table 1 and Figure 1 compare the characteristics of these two sensors. The TM provides narrower spectral bands, three of which are similar to MSS and four of which are new. The spatial resolution (ground instantaneous field-of view) of TM is 30m in the reflective bands, as compared to 79m for MSS. The radiometric (measurement) sensitivity or quantization level for TM is 8-bit (256 levels) as compared to 6-bit (64 levels) for MSS data. Although the TM is basically a better version of the MSS sensor, it is believed that the technological advances of the TM sensor will support a more detailed analysis of the earth resources. Malila et al. (1984) provide a detailed description comparing these and other characteristics of MSS and TM digital image data.

Table 1. Landsat Thematic Mapper and Landsat MSS sensor characteristics.

Sensor Characteristic	Landsat TM	Landsat MSS
Spectral Band		
1	0.45–0.52um	0.5–0.6um
2	0.52–0.60	0.6–0.7
3	0.63–0.69	0.7–0.8
4	0.76–0.90	0.8–1.1
5	1.55–1.75	
6	10.40–12.50*	
7	2.08–2.35	
Ground IFOV (at nadir)	30 m	79 m
Quantization Levels	256	64

*The thermal band has an Instantaneous Field of View of 120 m.

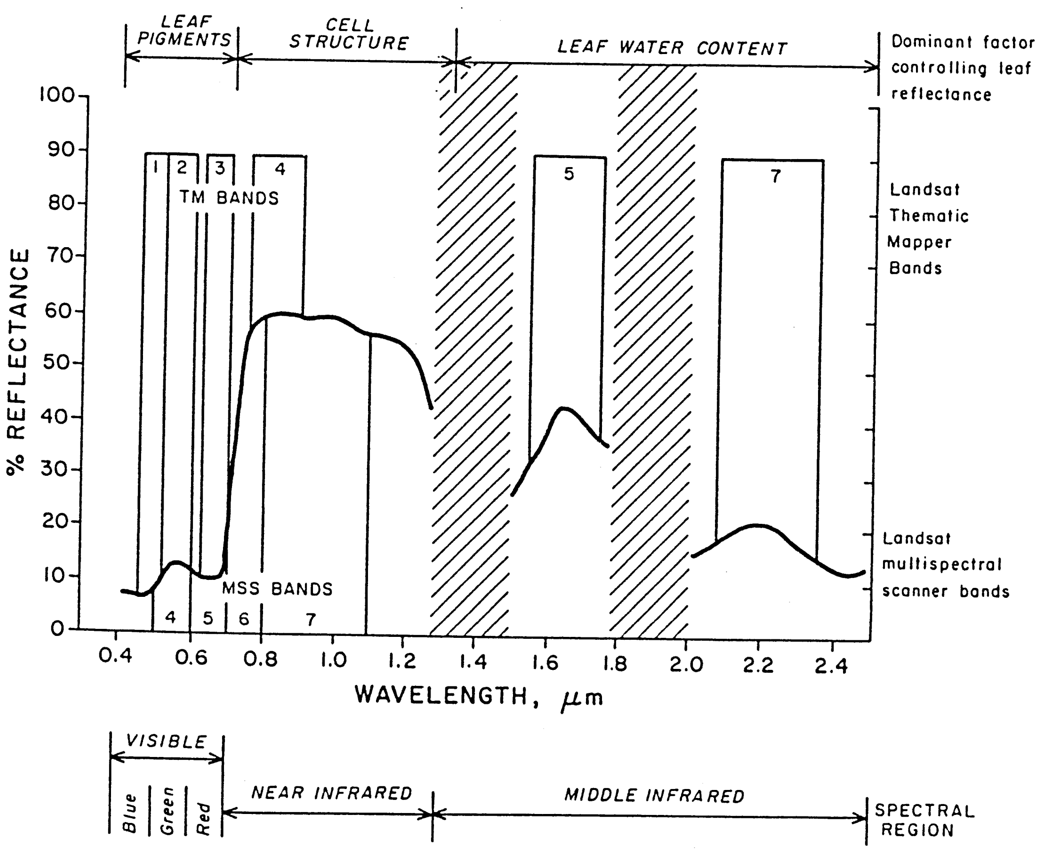

Figure 1. Typical vegetation reflectance curve with Landsat MSS and TM bands indicated. Gaps in the spectral curve at 1.4 and 1.9 um are caused by atmospheric water absorption.

2.3. Spectral Properties of Leaves and Canopies

Incident radiation is reflected, absorbed, or transmitted by vegetation. Leaves are the primary contributors to canopy reflectance. Reflectance is the phenomenon of most significance to remote sensing. Figure 1 illustrates the general reflectance patterns of vegetation, and the dominant factors controlling these patterns across the reflective portion of the electromagnetic spectrum.

In the visible portion of the spectrum (0.38–0.72 um) leaf reflectance is relatively low. Chlorophyll and other leaf pigments absorb incident energy in the blue (0.45 um) and red (0.67 um) wavelengths. If chlorophyll is reduced due to plant stress or senescence, there will be a resulting increase in leaf reflectance, particularly in the red region.

A substantial increase in leaf reflectance occurs in the near infrared (0.7–1.3 um) portion of the spectrum. Allen and Richardson (1968) demonstrated that leaves generally reflect 40 to 50 percent and absorb less than 5 percent of the incoming energy in these wavelengths. Near infrared reflectance (NIR) is controlled by the internal structure of the leaf, specifically the mesophyll cell structure. The high reflectance is a result of scattering at the interfaces of the spongy mesophyll cell walls. Many plant species and stages of plant development have distinct differences in their internal cell structure. They differ, therefore, in NIR reflectance even if differences in the visible reflectance are negligible (Sinclair et al., 1971). Multiple leaf layers or vegetation canopies have even higher reflectance, from

70 to 80 percent, in the NIR portion of the spectrum (Allen and Richardson, 1968). This phenomenon is due to additive reflectance where energy is transmitted through the uppermost layer of the canopy, and relected from a second layer. Figure 2 shows the significant increase in near infrared relectance as more leaf layers are added.

Water absorption and water content of leaves and plant canopies are the dominant factors controlling reflectance in the middle infrared bands (MIR) (1.3-3.0 um). Generally, as the moisture content of leaves decreases, reflectance in the middle infrared region increases. The reason for this is that water in the leaves is a good absorber of infrared radiant energy, so the amount of MIR energy absorbed by vegetation is a function of the total amount of water present in the leaf (Tucker, 1980). Much remains to be learned about the vegetation and water energy-matter interactions. Strong water-absorption bands occur near 1.4, 1.9 and 2.7 um; however, for remote sensing purposes we are primarily interested in the "atmospheric windows" in which satellite sensors can operate (1.6 um and 2.2 um) (Figure 1).

Thermal energy can also be detected by the latest satellite systems. Thermal energy differs greatly in its behavior and characteristics because it is emitted (heat) rather than reflected energy. The latest satellite system detects thermal energy between 10.40 and 12.50 um and at a spatial resolution (IFOV) of 120m.

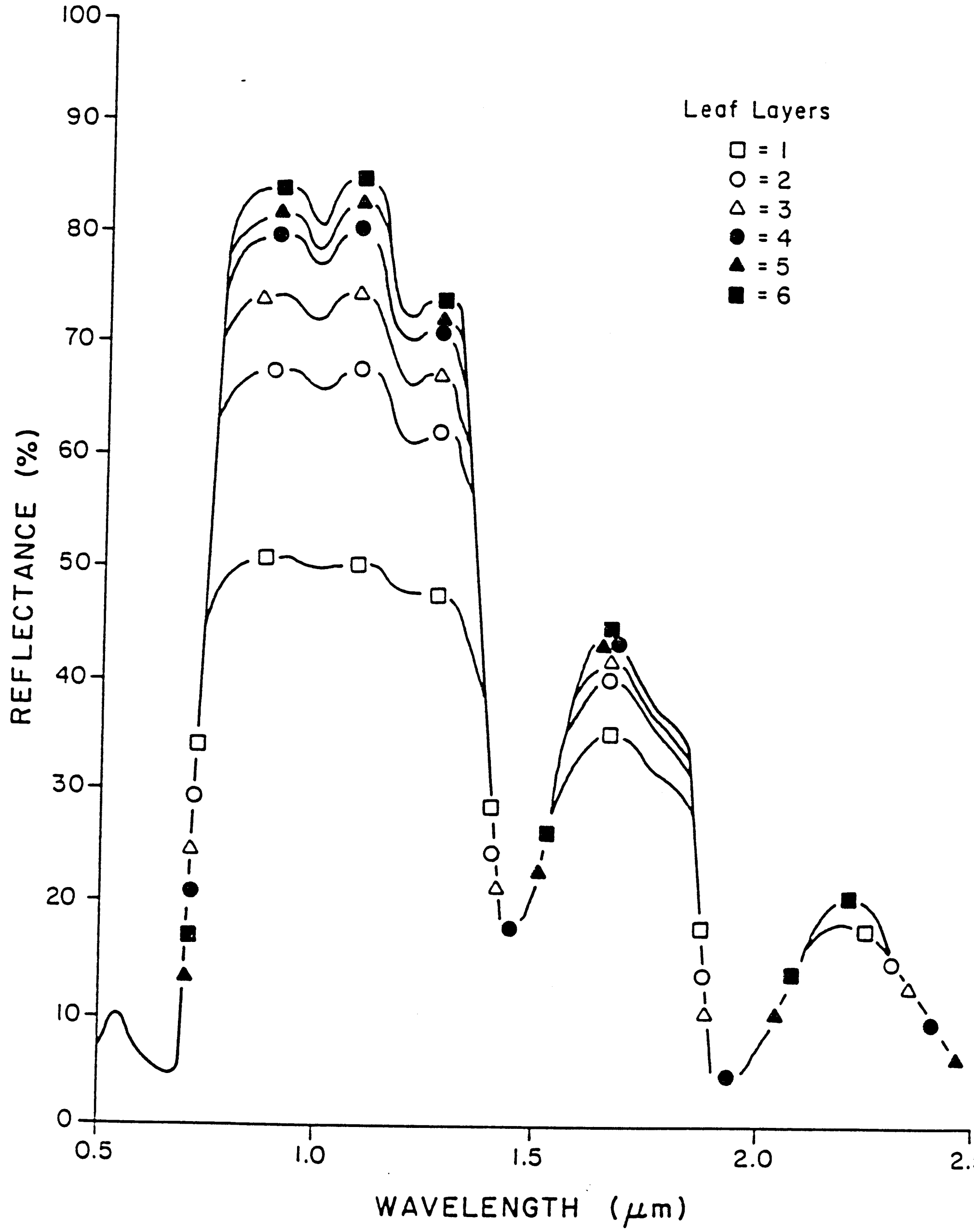

Figure 2. Effect of increasing number of leaf layers on reflectance spectra of cotton leaves (Allen and Richardson, 1968).

The spectral reflectance of forest and other vegetation canopies is determined by many factors, but there are five factors fundamentally responsible, including: (1) leaf optical properties; (2) canopy geometry, particularly leaf area index (LAI) and leaf angle distribution; (3) background reflectance (e.g., soil, litter, understory vegetation); (4) solar illumination; and (5) atmospheric transmittance (Bauer, 1985). Leaves are the primary scattering elements of the canopy when trees are fully leafed out. However, in early stages of growth, or when density is low, the background can significantly influence the overall reflectance. Reflectance is the phenomenon of most significance to remote sensing, and distinct controlling factors in reflectance are found among the visible, NIR, and MIR portions of the spectrum. Careful selection of the spectral bands available from the satellite sensors may improve the probability that a feature will be separated and identified during image analysis.

2.4. Effects of Spatial Resolution

Loosely, spatial resolution refers to the fineness of detail which is represented within an image. In the case of Landsat data it generally refers to the instantaneous field of view (IFOV) or pixel size of the sensor. The greater the resolution the greater the resolving power of the sensor system. Spatial resolution assumes different roles depending on the type of analysis that is performed. If the analysis is primarily photo or image interpretation, then spatial patterns become the major information-bearing attribute of the data. On the other hand, if the analysis is to be done on a multispectral basis (e.g., computer image processing), spatial resolution has a different role, and is not necessarily the major information-bearing attribute. The question of what spatial resolution is best (e.g., 79m MSS vs. 30m TM) depends primarily on the information classes required, and it is one question that was addressed in more depth in this study.

Increases in the spatial resolution of satellite-borne sensors will provide much more detailed data concerning the Earth's land resources. However, at finer scales, the variability in the size, shape, contrast, and spatial arrangement of land cover units also increases which might create more confusion between cover types. Much of the most recent remote sensing work uses computer-aided pattern recognition techniques for cover type discrimination. These techniques are highly dependent upon spectral rather than spatial properties of the target. Therefore, cover types that have "relatively high internal spectral variability relative to the differences between the land cover types, will not necessarily be identified with higher accuracy if resolution is improved (Forshaw et al., 1983)." This problem arises because the heterogeneities within a given cover type are often resolved and confused with other classes. This phenomenon is one contributor to "scene noise". Scene noise tends to be averaged out at coarser spatial resolutions and often results in higher classification accuracies at coarser resolutions (Markham and Townshend, 1981).

A second counteracting spatial factor, that occurs more frequently with coarser spatial resolutions, is the occurrence of boundary (mixed) pixels. Boundary pixels contain a mixed spectral response from two or more adjacent cover classes. This increasing percentage of boundary pixels at coarser resolutions will tend to decrease classification accuracies (Latty and Hoffer, 1981). There is, in fact, no *a priori* or theoretical basis for mixed pixels to be correctly classified when each pixel must be assigned to a single class.

A number of studies have examined these counteracting factors of scene noise and boundary pixels with varying spatial resolutions. These studies used aircraft scanner data which was progressively degraded to simulate coarser resolutions (Sadowski and Sarno, 1976; Townshend, 1981; Markham and Townshend, 1981; Latty and Hoffer, 1981). Figures 3 and 4 demonstrate that classification results vary with land cover type, and with the feature of interest within forest types with different spatial resolutions.

2.5. Image Processing and Feature Selection

2.5.1. Multivariate Statistics and Pattern Recognition

One primary objective of this study was to identify (or classify) the major forest (and associated) cover types in an area of north-central Minnesota using computer-aided techniques. This section will provide a brief explanation of pattern recognition theory and how this

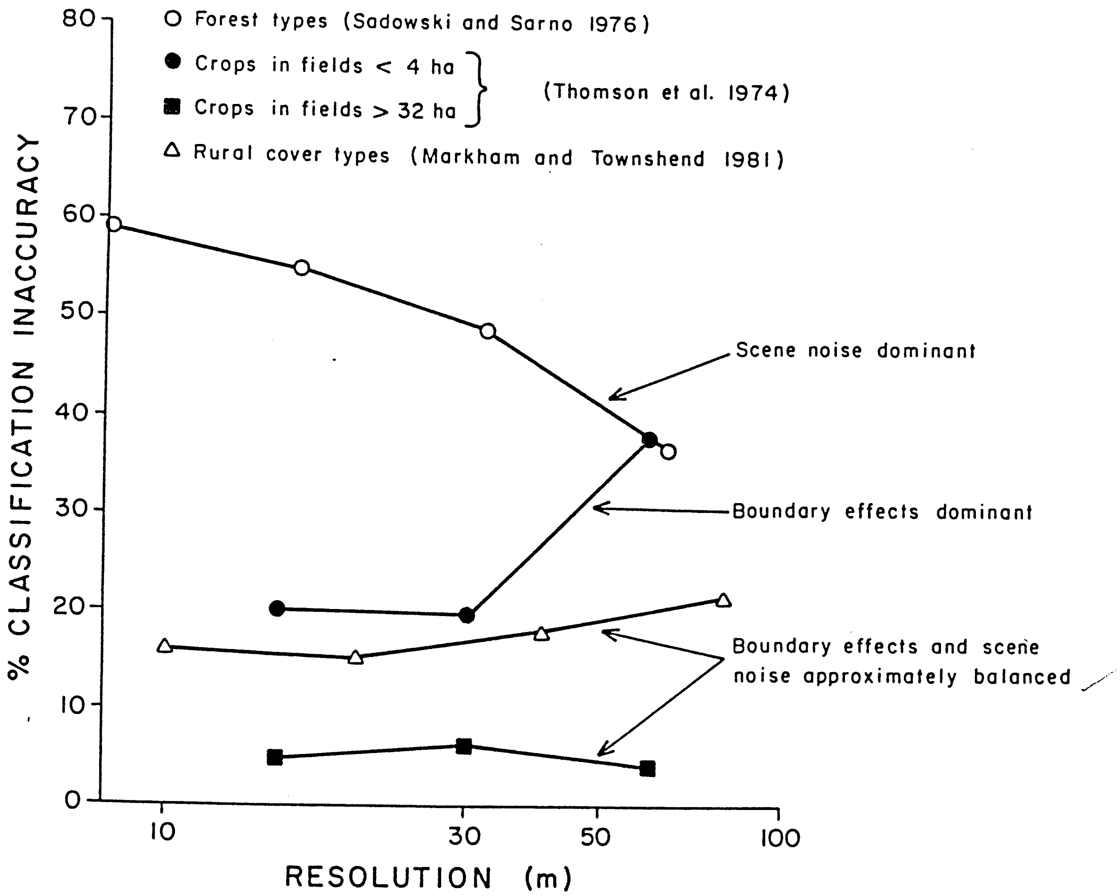

Figure 3. Changing classification accuracy with decreasing resolution showing interacting effects between scene noise and boundary frequency on classification accuracy (Townshend, 1981).

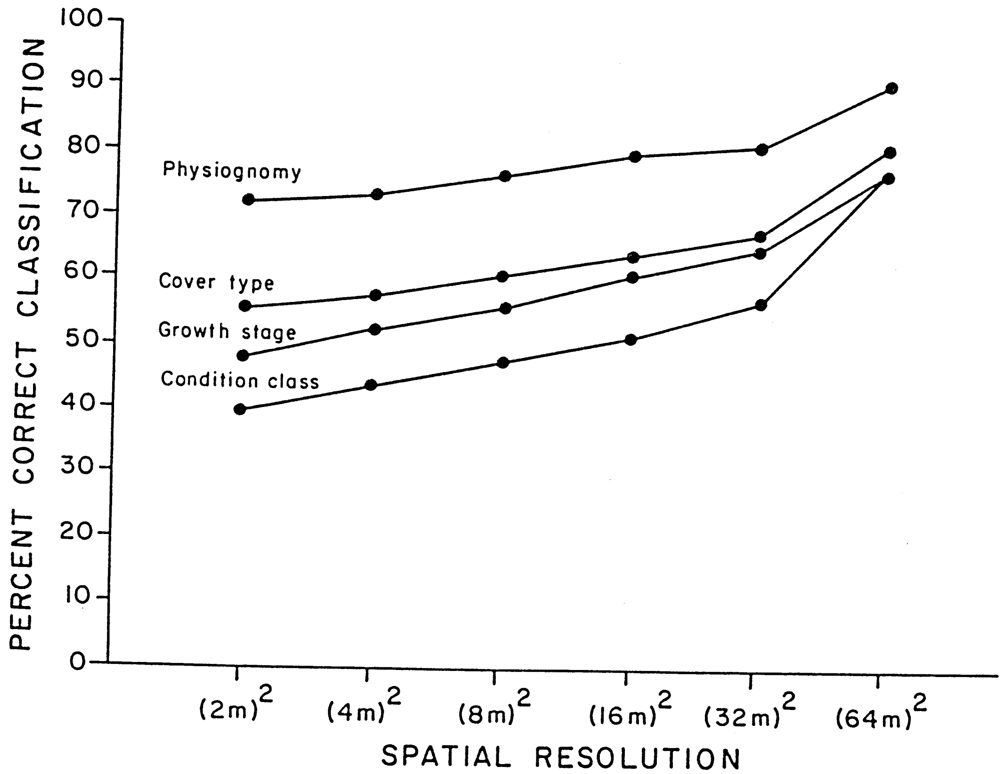

Figure 4. Classification accuracies for several hierarchies of forest features (Sadowski and Sarno, 1976).

theory is applied to spectral measurements obtained from satellite data.

Although the spectral response patterns of healthy vegetation tend to be similar there are variations within and between vegetation types. It is this variation between plant species that is of particular interest for classification purposes (Landgrebe, 1978). The problem, therefore, is deciding how to divide up this multivariate space so that a particular data point is correctly assigned to a discrete class. The most common approach is called "signature matching". A sample spectral signature, known as training samples, is obtained for each known cover type. The statistics (mean and covariance) developed from these training samples determine the decision boundaries in multivariate space. Any unknown spectral pattern is then classified into the decision region that it "best fits" using a specific decision rule. Many decision rules (classification algorithms) exist, the two primary algorithms used, however, are the minimum distance to the means and the Gaussian maximum likelihood.

The minimum distance to the means classifier first determines the average spectral value for each class of interest (mean vector). A pixel of unknown identify is classified by determining the distance between the value of the unknown pixel and each of the mean spectral values of the known classes. The unknown pixel (e.g., pixel 1 and 2) is then assigned to the class with the most similar value (Figure 5) (Swain, 1978).

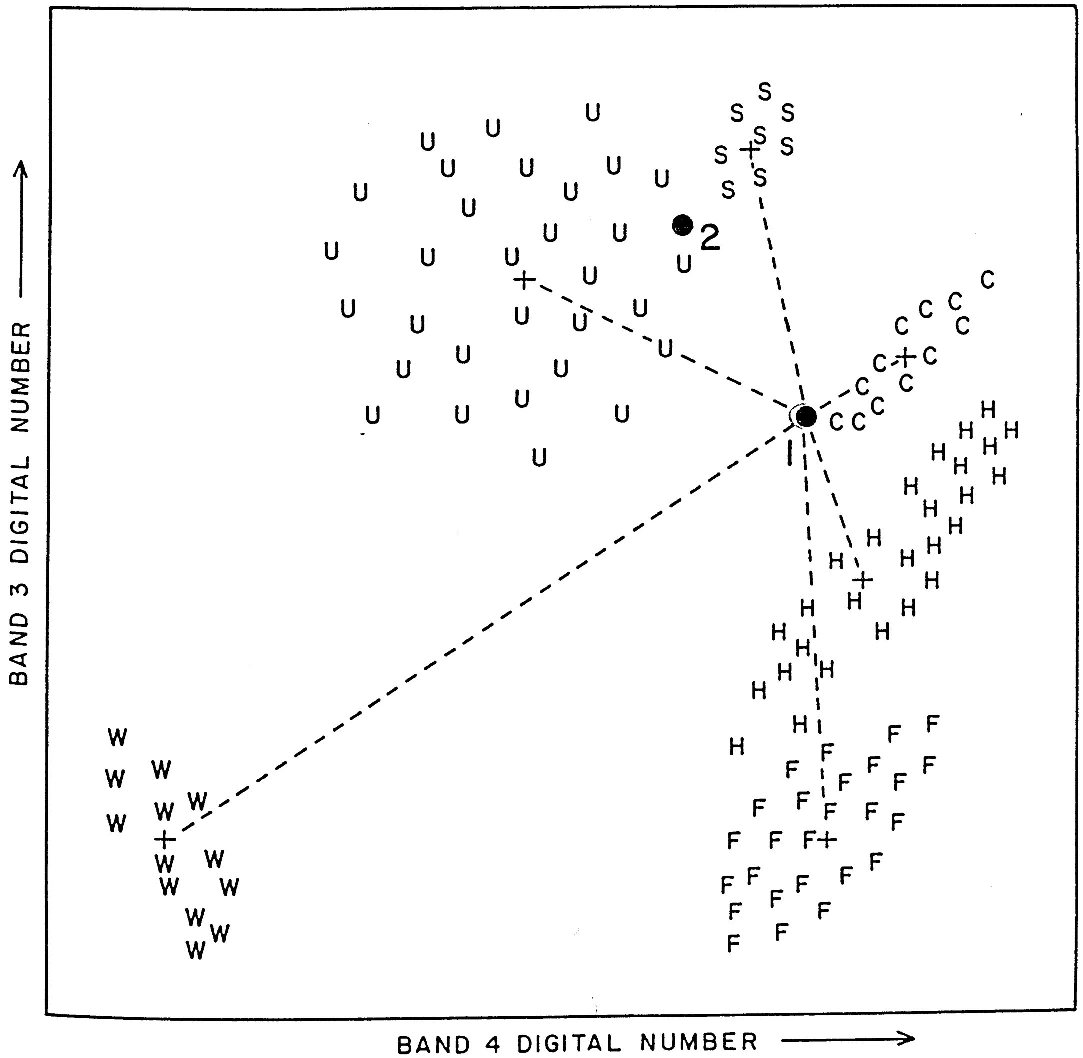

Figure 5. Minimum distance to means classification strategy. Unknown pixel 1 will be classified as cover type "C" while pixel 2 will be classified as cover type "S" (Lillesand and Keifer, 1979).

The maximum likelihood classifier uses both the mean vector and the covariance matrix (describing the variance and the correlation) of the unknown pixel to assign it to a particular class. An assumption made using this classification rule is that the spectral response distribution of the training samples is normal. Probability density functions (illustrated by equiprobability contours in Figure 6) are used to classify the "likelihood" that an unknown pixel (e.g., pixel 1 and 2) belongs to a known cover class. The large number of calculations required to classify each pixel makes this classification process slower and more expensive than the minimum distance to the means classifier; however, it is frequently more accurate (Swain, 1978).

2.5.2. Supervised Approach vs. Unsupervised Approach

The two basic computer-aided techniques for analyzing satellite data are supervised and unsupervised. The supervised approach requires that the analyst "train" the computer on samples selected from known cover types. The statistics gathered from the training samples are then used as the basis to classify the remaining pixels in the scene. The classification procedure will perform relatively well if the training classes are representative and have significantly different spectral signatures. If the classes are spectrally very similar the classification procedure will have difficulty producing accurate results.

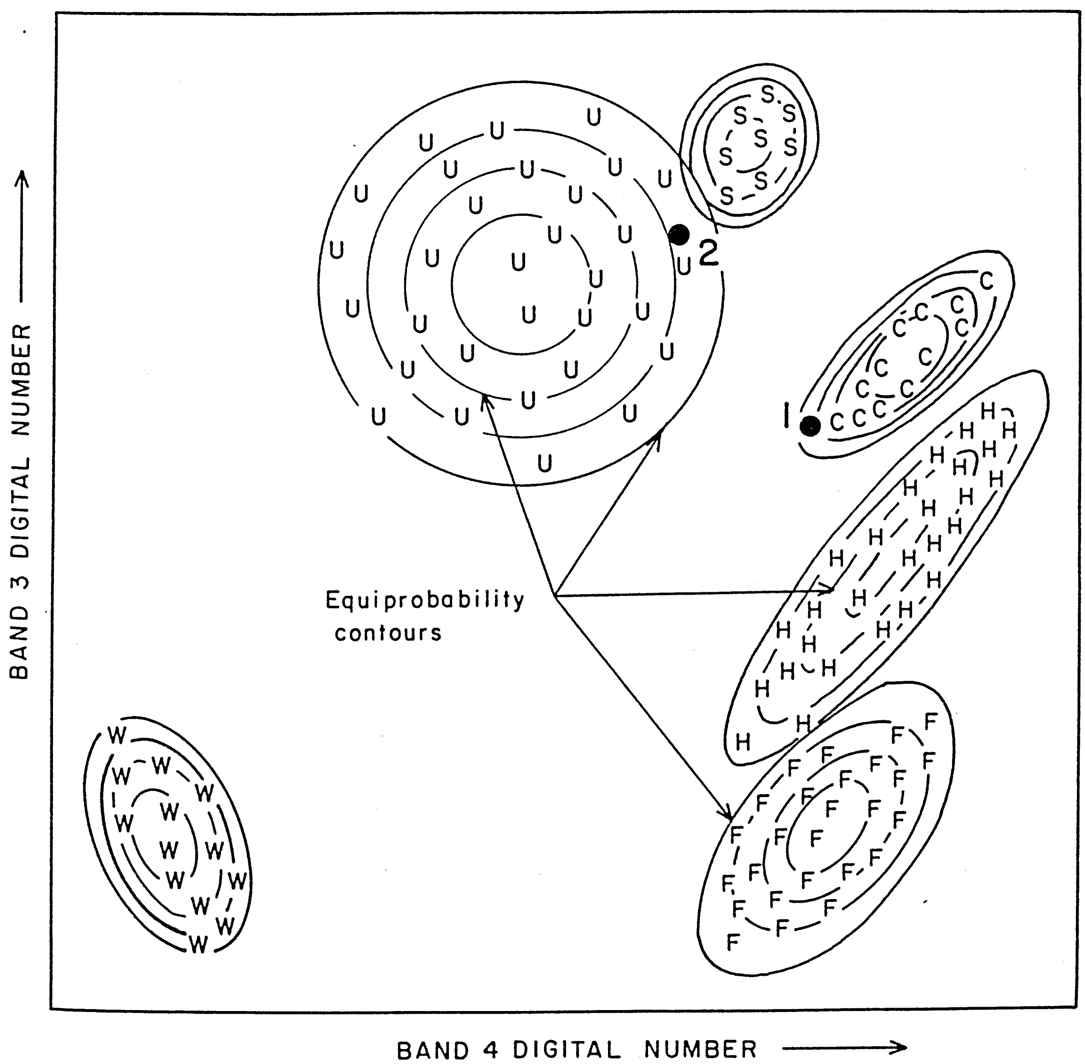

Figure 6. Equiprobability contours defined by a maximum liklihood classifier. Unkown pixel 1 will be classified as cover type "C" while pixel 2 will be classified as cover type "U" (Lillesand and Keifer, 1979).

The unsupervised or clustering approach does not use analyst-specified training statistics. In this approach the unknown pixels in the scene are divided by a "clustering" algorithm into a number of classes based on natural groupings present (e.g., similarities in mean spectral values). The basis of this approach is that similar cover types should yield similar spectral values, and therefore should fall close together in the measurement space. The identity of the natural groupings is not known and the analyst must subsequently assign an information class to them. "Thus, in the supervised approach we define useful information categories and then examine their spectral separability; in the unsupervised approach we determine spectrally separable classes and then define their informational utility (Lillesand and Kiefer, 1979).".

Many studies have been conducted to compare the supervised and unsupervised approaches to training the computer for computer-aided analysis (Fleming and Hoffer, 1975). Each approach has its advantages and disadvantages. The supervised approach has the advantage of the analyst choosing the information classes (training samples) and therefore interpreting the spectral classes that result. In complex cover types however, it takes time amd painstaking effort to develop enough training statistics to adequately represent all of the variation inherent in the scene.

With the unsupervised approach, the major advantage is "automatically" obtaining the training classes, this is particularly important if little is known about the spectral characteristics of the cover types present. This approach also optimizes the separability between classes (Coggeshall and Hoffer, 1973). The disadvantages are that the analyst must select the number of spectral classes required; there may be difficulty in defining the spectral classes that result from the clustering; and more computer time and memory may be required than for the supervised approach.

The results in the literature studies are rather inconclusive regarding which approach is better for classifying forest cover types. Kalensky (1974), Hoffer (1975), Fleming et al. (1975), Mroczynski et al., (1980), report varying success (a range of 67 to 81% accurate classification with broad classes such as coniferous or deciduous forest, grassland, etc.) with either the supervised or unsupervised approach.

2.5.3. Feature Selection and Data Transformation

Frequently with remote sensing studies there is an overabundance of spectral data in other words, not all spectral bands are necessary to provide adequate separability of the cover types to be classified. Since the cost of computer classification increases geometrically as more features (e.g., spectral bands) are added, there is some motivation for finding the minimal number of features that are needed to accurately classify the desired classes in a particular scene. This process of separating the most useful spectral features from the features which are redundant, and thus reducing the dimensionality of the data to simplify the calculations, is called feature selection and extraction (Swain, 1978).

The two feature extraction techniques that I used in my study are feature subset or selection, and a linear combination of spectral bands called Greenness-Brightness or the Tasseled-Cap transformation. With feature selection the analyst chooses the subset of spectral channels (or whatever variable) that will yield the highest classifica- tion performance at the lowest cost. Oftentimes a statistical test of feature separability called divergence is used to make this choice. As I did not have such a test available to me; I made my choice of channels based on studies in the literature. Although it might seem reasonable to assume that one should use all the spectral channels available, many studies have demonstrated that in practical situations involving limited training data, one does not necessarily obtain higher classification accuracy by adding channels (Fu et al., 1969, Figure 7).

Forest classification studies reported in the literature differ in the choice of optimum number and wavelength of spectral bands. Studies using MSS data have shown that the visible bands (1 and 2) are highly correlated, as are the near infrared bands (3 and 4). Therefore, it is often suggested that an analyst use one visible and one near infrared band. The situation becomes more complicated with the choice of TM bands. Latty and Hoffer (1980), using aircraft-acquired Thematic Mapper Simulator (TMS) data for forest types in South Carolina, gained little in terms of species separation by using more than four channels. Their results indicated that bands 1

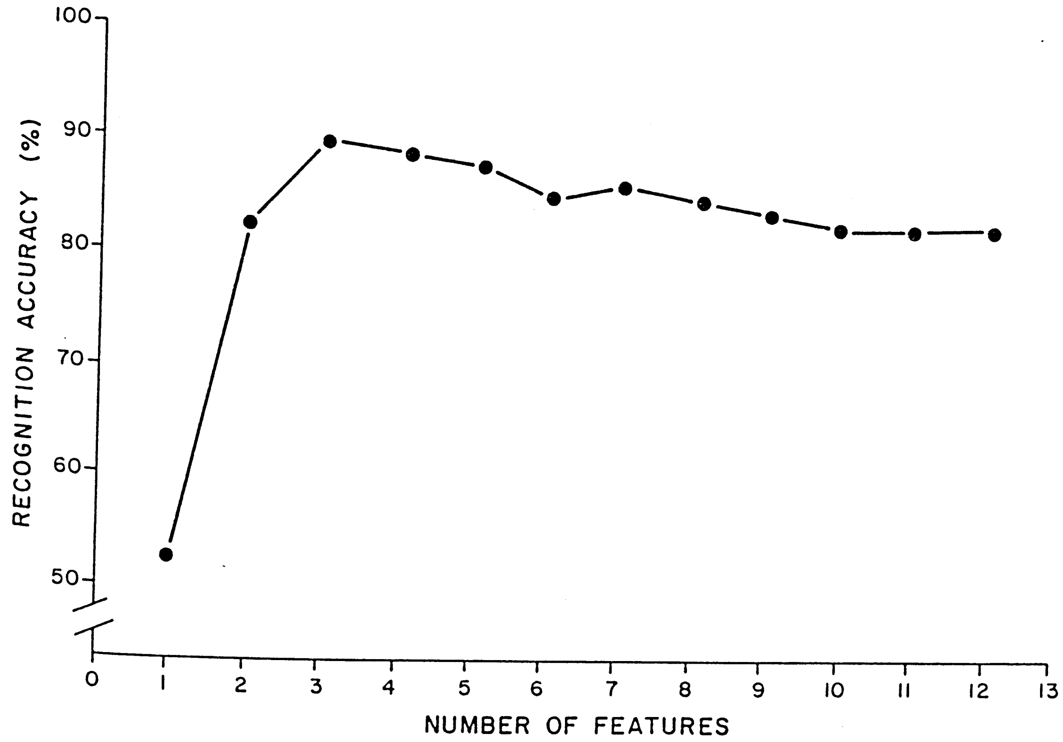

Figure 7. Experimental results showing accuracy versus the number of optimally selected features (Fu et al., 1969).

1, 3, 4, 5 or 7

(blue), 3 (red), 4 (near infrared), and one middle infrared (either 5 or 7) gave the best results. Lillesand et al. (1985) used all seven TM bands to classify eight agricultural, seven nonforest, and nine forest classes in northern Wisconsin, although they mentioned that band 5 often provided the most separation between forest classes. Brass et al. (1983) recommended bands 4, 6 (thermal), 5 and 3 for identification of conifer types in Idaho. Nelson et al. (1984), after conducting a study using TMS data in north central Maine, suggested that the best four bands were 4, 1, 5, 7. They determined that the first middle infrared band (5) was the best for cover type discrimination and the second middle infrared was best for delineating conifer defoliation. Teillet et al. (1981), using TMS data for conifer delineation in British Columbia, suggested the three optimum bands to be 1, 3, 4, and four optimum bands to be 1, 3, 4, 6. Teillet concluded that band 1 differentiated western forest types, band 3 differentiated forest insect damage, and that band 4 was needed for all cover type discrimination. In most cases he found no advantage to increasing the number of channels beyond three. In western Ontario, Holler and Ahern (1986) determined that bands 3, 4, 5 were best for general cover type discrimination, and that bands 1, 4, 5 were marginally better for separating a set of softwood classes, even though band 1 has a very small dynamic range. They found that the middle-infrared bands (5 and 7) were particularly sensitive to forest vegetation density. Jackson (1983) concluded that the near infrared (band 4) and one middle-infrared band (either band 5 or 7) in any combination of channels contributed most to vegetation discrimination.

What can be determined from these studies is that the choice of spectral bands is highly dependent on data and application. It appears that in all cases, however, a choice of at least one visible, one near infrared, and one middle infrared channel is necessary for optimum results in vegetation discrimination. The thermal band would probably add additional information (Kumar and Silva, 1973), but the lesser spatial resolution (larger pixel size) of the Landsat TM thermal data complicates its use.

Many data transformations exist which reduce the dimensionality and normalize remotely sensed spectral data (Tucker, 1979; Richardson and Wiegand, 1977; Jackson, 1983). The Tasseled-Cap or Greenness-Brightness transformation developed by Kauth and Thomas (1976), however, is considered to "be a major advancement in capability to effectively work with multispectral data (Bauer, 1985)." It is a linear transformation that is effective both in data compression and enhancement of crop identification accuracies, yet has not been tested to any extent for forest type classification.

The Tasseled-Cap transformation is a linear transformation that rotates the data in a manner similar to principal component analysis. If MSS data are transformed then most of the information content of the data (95% of the total variability) are contained in two features (or axes) that are directly related to physical characteristics of the scene. The first axis, called brightness, is a weighted sum of all the spectral bands. It is strongly related to varying soil background and illumination conditions. The second axis is a weighted difference between the NIR and visible bands, is approximately orthogonal to brightness, and is strongly related to the amount of green vegetation in the scene. This feature is called greenness.

Crist and Cicone (1984a) describe the behavior of greenness. "Greenness responds to the combination of high absorption in the visible bands (due to plant pigments - particularly chlorophyll), and high reflectance in the near infrared (due to internal leaf structure and the resultant scattering of near infrared radiation) which is characteristic of green vegetation" (Figure 1). Numerous studies with agronomic crops have shown moderate to high correlations of measures of amount of green vegetation, such as percent canopy closure, leaf area index, and fresh biomass, to greenness.

This transformation has also been applied to the reflective bands of Landsat TM data (Crist and Cicone, 1984b). The brightness and greenness axes are the same as those in MSS data, but a third feature, called wetness, may contain new information related to soil and vegetation canopy moisture. The Greeness-Brightness transformation was used in this study to determine its usefulness for delineating forest cover types.

2.6. The Temporal Dimension

2.6.1. General

Temporal data allows researchers to capitalize on the changes that occur over a certain time period, thus gaining an added dimension that may lead to improvement in classification. Recent studies of agronomic crops have produced significantly better results by combining multidate data from MSS and simulated TM data than using single date information alone (Hay et al., 1982; Badhwar et al., 1982; Hixson et al., 1982). Although researchers working with forest vegetation certainly recognize the importance of seasonality, relatively few studies have actually combined two or more different dates of MSS data (Kalensky and Scherk, 1975; Kan and Dillman, 1975; Williams, 1976; Mead and Meyer, 1977; Lee, 1980; Merola et al., 1983; Lozano-Garcia and Hoffer, 1985). Most of these studies report relatively little gain in using multidate data, while others report as much as 11 percent increase in classification accuracy. This discrepancy may be due to the fact that combined data sets often require more training data (samples) to adequately represent the classes in multivariate space. The more channels that are added to the temporal data set, the greater the possibility of diluting important information by adding insignificant data. This phenomemon was discussed in more detail under feature selection (section 2.5.3.). Although progress has been made, there is still much work to done in this significant area of research to identify optimum dates to collect remote sensing data.

2.6.2. Stacked Vector

Multitemporal data analysis using the stacked vector approach is identical to multispectral data analysis. The images are spatially coincident and consist of digital numbers taken from different dates as well as different spectral bands. The same analysis procedures are used to interpret the multidate data set as are used on single-date multispectral data.

The use of feature selection is usually appropriate since the multidate approach increases the number of bands to be analyzed. In this study, for example, we have four or five dates of TM data to analyze. This creates a matrix of five dates times seven bands or 35 layers (or channels) of data. We can only analyze eight channels at a time with our system, however, and therefore we must reduce the dimensionality by choosing the optimum bands (feature selection) or through the use of a transformation.

Precise, pixel by pixel registration of image data from different dates is necessary when conducting multitemporal analysis. This registration, requiring accurate geometric correction of the imagery, is relatively easy and precise using satellite data.

2.6.3. Temporal Profile Model

Multitemporal spectral profiles (Badhwar et al., 1982) are used in agriculture to classify crop types. This approach is used to model the time behavior of crop spectral response over an entire season. The

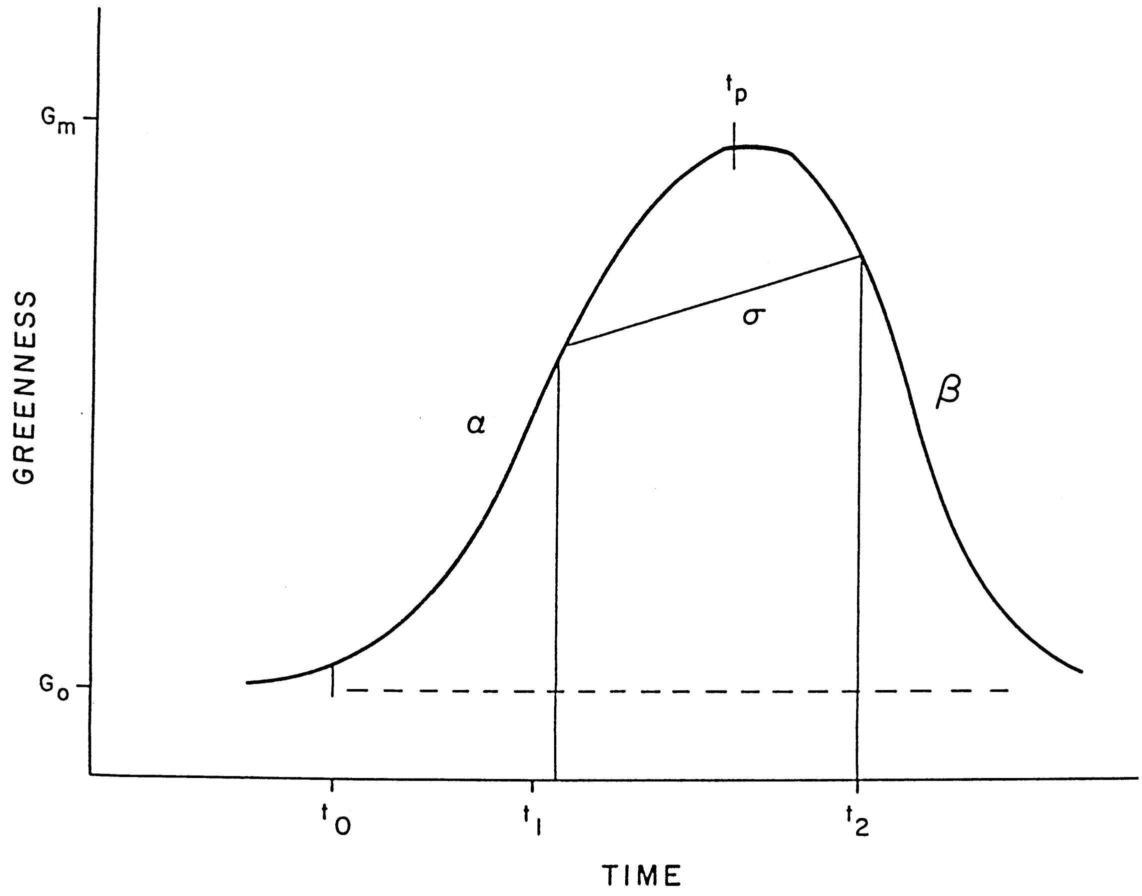

Figure 8. Temporal profile for greenness. Key parameters include: spectral emergence date – to; time of peak greenness – tp; and the width of the profile – σ. Alpha (α) and beta (β) are related to rates of green-up and senescence, respectively (Badhwar, 1984).

model uses the greenness feature from the Greenness-Brightness transformation. Several studies have demonstrated that the time behavior of greenness for annual crops is sigmoidal and that the greenness of soils in a particular area is nearly constant (Badhwar, 1985). The temporal behavior of greenness has a strong physical link to crop characteristics (Bauer, 1985).

The greenness profile model is illustrated in Figure 8. Badhwar represents the greenness profile in time using data from small grains, corn and soybeans as:

$$G(t) = G_0 (t/t_0)^{\alpha} \exp[\beta(t_0^2 - t^2)] \qquad [1]$$

where, G_o is the soil greenness at date t, t_o is the spectral emergence date, G(t) is greenness at time t, and α and β are crop specific parameters related to rates of change in greenness early in the season and at the onset of senescence. These parameters are estimated by first transforming the multidate data into greenness, then greenness is fitted to the profile model using either linear or nonlinear regression techniques. Thus the dimensionality of the data is reduced from 20 dimensions (assuming five MSS acquistion dates) to three dimensions, α, β, and t_o.

A more general form of the model has been developed which extends its capabilities (Badhwar, 1984):

$$G(t) = G_0 + (G_m - G_0)(2\beta e/\alpha)^{\alpha/2} (t-t_0)^{\alpha} \exp[-\beta(t-t_0)^2] \qquad [2]$$

where G_o is the soil greenness, α and β are crop and condition specific constants, t_o is the date of spectral emergence, G_m is the maximum greenness at time $t_p(=\alpha/2\beta)$. The model has two inflection points, t_1, and t_2, which are related to rates of change in greenness. The difference between t_1, and t_2, called σ, is:

$$\sigma^2 \equiv (t_2 - t_1)^2 = 1/2\beta + \alpha/2\beta[1-(1-1/\alpha)^{1/2}] \simeq 1/\beta \qquad [3]$$

The features, G_m, t_p, and σ account for more than 95% of the information in the original data. Points t_1, t_p, and t_2 are related to crop development stages (Bauer, 1985).

This model has been used to successfully separate summer and non-summer crops, and discriminate between corn and soybeans with a high degree of accuracy (e.g., 75-85%) (Badhwar, 1984 and 1985). Few crop classification studies have been investigated using TM data; however, Badhwar (1985) achieved 10% higher accuracy than previously achieved with MSS data using TM data and the temporal profile approach to classify crop types in Iowa.

The applicability of the multispectral temporal profile model approach is a new idea to be investigated for the classification of forest cover types. The link between spectral data, biophysical characteristics, and the time behavior of greenness make the use of this model for discriminating forest types an attractive possibility. Two studies have examined leaf area index and species separability of boreal species using TMS and canopy reflectance models (Shen et al., 1985; Badhwar et al., 1986). There is only one other study that I am aware of that is examining the use of temporal profile models for forest cover-type classification (F. Hall et. al., 1986, pers. comm.). Hall's research is being conducted at the Earth Resources Branch NASA Goddard Space Center using MSS data, while our research is using TM data.

2.7. Forest Classification Using Satellite Data—Selected Studies

2.7.1. General

Although remote sensing techniques can complement land classification systems, questions are often raised concerning the accuracy and limitations associated with the use of Landsat data for obtaining detailed land and forest cover type information. The complexity of the forest ecosystem is exhibited in the spectral, spatial, and temporal characteristics of the satellite imagery, and is the primary reason for the varying success of forest land classification studies which utilize computer-aided analysis techniques. Most of the early studies using satellite data to classify forest cover types relied completely on spectral differences. More recent research has attempted to increase classification accuracies with the addition of temporal, spatial, and ancillary (non-spectral) data. Studies investigating the use of MSS data for forest classification are numerous, yet those examining the usefulness of TM data are relatively scarce.

2.7.2. Multispectral Scanner Studies

The use of Landsat multispectral scanner imagery (MSS) to classify general land use and broad forest classes has been tested by many researchers (Coggeshall and Hoffer, 1973; Heller, 1975; Hoffer and Staff, 1975; Anderson et al., 1976; Mead and Meyer, 1977; Kan and Weber, 1978; Strahler et al., 1978; Rohde, 1978; Fleming and Hoffer, 1979; Mazade et al., 1981; and many others). There have also been a few studies which have attempted to spectrally identify forest cover types to a dominant species level (Hoffer et al., 1979; Walsh, 1980; Mayer and Fox, 1981; Fox et al., 1983; Hame, 1984). Several investigators have attempted to use satellite data in their studies of ecological land classification (Jurdant et al., 1973; Thie and Ironside, 1976; Lopoukhine et al., 1978; Mueller-Dombois, 1984). Classification accuracies for these studies have had varying results although the accuracy of forest cover type identification has often been disappointingly low. Satellite imagery cannot gain credibility as a part of a forest manager's data base or as an essential part of an ecological land classification until it becomes a consistent, reliable source of information.

I will discuss results from selected studies that investigated the use of Landsat MSS data, with emphasis on studies from Minnesota and other Great Lakes states. Results of these studies demonstrate the high variability inherent in using satellite data to classify forest cover types. In Itasca Co., Minnesota, Eller et al. (1973) successfully delineated forest and nonforest categories using manual aerial photo interpretation techniques. Eller et al. (1974), using enhanced imagery and manual techniques, concluded that conifer versus hardwood classes were the most detailed delineations possible in northern Minnesota.

Digital analysis techniques have been used by many researchers. Kirvida (1973) classified six land-cover classes in Itasca County, Minnesota, and achieved accuracies between 70 and 90% on training sets. In New Hamshire, Dodge and Bryant (1976) obtained results comparable to existing forest maps of the region and were able to separate mixed softwood-hardwood stands into three cover classes (75% softwood-25% hardwood, 50% softwood-50% hardwood, 25% softwood-75% hardwood). Mead and Meyer (1977) mapped eleven categories of land cover in northern Minnesota that were relatively broad types (e.g., lowland conifer, brush and shrub, sedge meadow etc.) and obtained 43-53% overall accuracy. They concluded that classification accuracy of forest land cover types was inadequate for extensive (or intensive) use by field level resource managers.

Mroczynski et al. (1980) evaluated areas in Carlton County, Minnesota, to compare Landsat MSS classification results to current survey statistics for forest/non-forest classes in the northeastern aspen-birch survey unit. They obtained 82 to 85% classification accuracy and 10 to 14% difference in areal estimates. Roller and Visser (1980) generated a forest cover map of Lake Co., Michigan, and attempted to identify fairly detailed cover-type categories (e.g., red and white pine, northern hardwoods, marsh, oak, etc.). They obtained accuracies for individual categories ranging from 27% for oak-aspen, 36% for hardwood reproduction and brush, 56% for red and white pine, and 59% for northern hardwoods. Their conclusion from this study was that "it does not appear possible to map tree species or species-groups in the Lake States using automated methods (and MSS data) with acceptable accuracy."

Downs (1981) investigated an area in Carlton County, Minnesota (Cloquet Forestry Center), using Landsat MSS data for forest cover type mapping. Classification performance on training sites yielded an average accuracy of 94% on classes such as conifers (jack and red pine), lowland conifers (black spruce, tamarack), marsh, upland hardwoods (aspen and birch) and cutover. Performance on more heterogeneous areas, however, dropped to an average of 45% class accuracy and 60% overall accuracy.

Using MSS data and the unsupervised classification approach for forest cover type separability, Duell (1982) evaluated several study areas in Beltrami and Hubbard Counties, Minnesota. The unsupervised clustering algorithm discriminated among 22 spectral classes. The cross-over and spectral confusion among forest cover types necessitated the aggregation of these 22 classes into five: deciduous, coniferous, mixed, nonforest, and water. Classification accuracy results were as follows: deciduous 57-98% correct; coniferous 59-67%; mixed 59-65%; nonforest 87%; and water 89-92%. The ranges reported here are simply the highest classification accuracies from the two study areas (counties) that Duell investigated. Duell concluded that the "use of

Landsat MSS for mapping forest cover types of northern Minnesota seems to be very limited."

The accuracy of delineating and classifying forest cover types using MSS data, especially in the Lake States, have been disappointingly low. Low classification accuracies can be attributed to many factors, specifically the coarse spectral and radiometric resolution. Therefore, researchers have recently turned their attention to Landsat TM data which has higher spatial, spectral, and radiometric resolution.

2.7.3. Thematic Mapper Studies

Relatively few studies have been conducted on the use of actual TM data for forest cover type classification and mapping since it is a newer sensor. Most of the research thus far has used Thematic Mapper Simulator (TMS) data . Teillet et al. (1981) used TMS data in a very mountainous area of British Columbia that had lodgepole pine, Douglas fir, and mixed Douglas fir and ponderosa pine cover types. Using the above classes as well as classes such as rock, bare ground, and water, they obtained a range of accuracies from 55-100% with 83% overall accuracy. Some forest types were identified with as much as 20-25% more accuracy with TMS than MSS data.

Dean and Hoffer (1982) used TMS data to classify an area in South Carolina into pine, hardwood, tupelo, clearcut, pasture, crop, soil, and water. Using the best three (TMS 1, 3, 6) and best four (TMS 2, 4, 5, 7) bands, they obtained a range in overall classification performance of 65-90% accuracy.

In the Clearwater National Forest in Idaho, Brass et al. (1983) used TMS data to classify a forested scene. They had three levels of categorization—resource category (15 classes, e.g., urban, water, agriculture, mixed conifer) crown closure category (4 classes of crown closure plus clear cut), and size class category (e.g., sawtimber and pole). Their results for a range of classification accuracies were 45-55% for the resource category, 58-64% for the various crown closures, and 62-74% for the size class category.

Nelson et al. (1984) attempted forest cover classification in Baxter State Park (Maine) using TMS data. Classification accuracies peaked at 58% for 13 Level II/Level III classes (e.g., clearcut, old clearcut, hardwood, conifer, mixed wood, bog, blowdown, stripcut, meadow, water, three classes of defoliation, etc.), and 65% for Level II/Level III after the number of classes had been aggregated to ten (e.g., by combining clearcut and old clearcut, conifer and mixedwood, and severe and heavy conifer defoliation). Levels I, II, and III (Anderson et al., 1976) refer to a land classification scheme for remote sensing data, where Level I includes very broad classes (e.g., forest/non-forest), Level II is slightly more specific (e.g., conifer, hardwood, etc.), and Level III refers to specific cover types (e.g., aspen, red pine, clearcut, etc.).

In the Plumas Forest of northern California, Benson and DeGloria (1985) evaluated actual TM data for forest classification using traditional interpretation techniques applied to imagery (film) and hardcopy digital products. The classes included in this study were high-density conifer, hardwood/conifer, hardwood, brush, meadow, grassland, bare ground and rock. Various TM band combinations yielded different accuracies. Interpretation of the image of TM band combinations 2, 3, 4 and TM 3, 4, 5 yielded the highest average accuracy values for the hardwood/conifer class (57%) and the brush class (80%), respectively. TM band combination 2, 3, 5 yielded the highest average classification value of 67% correct for the grassland class. Accuracies ranged over these eight classes from 20-90% correct.

Lillesand et al. (1985) used actual TM data for forest classification research in northern Wisconsin. They had 26 categories, including eight agricultural, seven nonforest (e.g., water, marsh, cloud etc.), and nine forest types (e.g., white pine, red pine, Norway spruce, lowland conifer, lowland hardwood, aspen, tamarack/alder, oak/northern hardwoods, central hardwoods). They created three reference "subgroups" from their scene, each containing polygons from each of the 26 categories. Two reference subgroups were used for training and the third was reserved as an independent test ("test fields") sample. Using the supervised classification approach and all seven TM bands, they achieved 98% overall accuracy for non-forest/forest classes; 94% overall accuracy for hardwood/softwood classes; and an average accuracy of 69% for the nine most detailed forest classes.

In an area near Ely, Minnesota in the Superior National Forest, Shen et al. (1985) conducted a study of sub-boreal forest species. Using TM Simulator data, they trained and classified on pure homogenous stands of aspen, birch, red pine, jack pine, and black spruce. They concluded that the results obtained represented a "best case" situation. Using all the simulated TM reflective bands, the overall percent correctly classified for all five species combined was 84%; coniferous/deciduous separation 97%; among coniferous species 86%; and among deciduous species 87%. Using an independent data set (but, homogeneous stands) they achieved the following overall accuracies for individual bands: band 1 - 43%; band 2 - 54%; band 3 - 50%; band 4 - 68%; band 5 - 51%; band 7 - 41%; and all bands - 80%. This study also investigated two dates (June and August) in relation to leaf-area-index information.

The study presented here represents the first attempt to classify forest cover types in Minnesota for practical inventories using actual TM data.

2.7.4. Comparison of MSS and TM Results

The studies conducted with actual and simulated TM data indicated that TM classification results were superior to MSS data for forest cover type delineation and classification. However, coincident sets of TM and MSS data must be analyzed to directly compare (both on an absolute and relative basis) the effectiveness of the two sensors.

Several studies have been conducted to quantify the effect of TM sensor improvements (various spectral, radiometric combinations) on classification accuracy over broad land-use classes. Williams et al. (1984) investigated an area near Washington D.C. and divided it into Level II/III land cover categories. Some of these categories included: water, agricultural-miscellaneous crops, corn-standing, corn-stubble, shrubland, soybeans, bare soil, hardwood forest, conifer forest, residential, and industrial/commercial. Overall classification accuracies reported for these 17 classes were 21% for actual MSS data and 37% for TM data (30m, 6 bands). The 17 classes were then aggregated into five Level I/II categories (i.e., water, crops, pasture/grass, forest, and urban). Overall accuracies for these five classes were 55% for actual MSS and 72% for TM data. The investigators attributed the low accuracies to the particularly rigorous experimental design used (which minimized analyst bias), and to the time of year (November) that the data were collected.

Despite these relatively low accuracies, other significant results from this study include: (1) simulated MSS (TM data that was degraded to 80m and same spectral bands) was 6.2% higher in classification accuracy than actual MSS data; and (2) comparison of real TM data (30m, 6 bands) resulted in a 16% improvement in classification accuracy in favor of the TM data. The latter increase in accuracy is attributed to the increase in spectral resolution (which was statistically significant) rather than the increase in spatial resolution (which was not statistically significant).

Schmidt and Naugle (1985) compared the results of TM and MSS data over an area in Calloway and Graves Counties, Kentucky. Their emphasis was on comparing supervised and unsupervised techniques. Using four land cover classes (water, forest, grassland, and cropland), they achieved their highest results (98% accuracy) with supervised classifications and TM data. An unsupervised classification from the same date comparing MSS to TM found the MSS results to be significantly less accurate (MSS=66%; TM=90%).

Toll (1985) assessed selected sensor parameter differences between TM and MSS through classification performance of a suburban/regional test site. Major cover types in the area included water, transportation, industrial, and residential. Overall classification accuracy of a seven-band Landsat TM scene, in comparision to MSS, yielded an increase in accuracy of 8% (from 75 to 83%). To study the possible causes for the difference in classification performance key parameter differences were investigated. Comparison of simulated MSS (TM data degraded to 79m, 3 bands) with actual MSS data for a November date, indicted a similar overall classification accuracy of 69%. Toll also concluded that of the two sensor parameters contributing to a higher accuracy, spectral bands and quantization, the added spectral regions are of more importance. When adding TM bands 1 (blue), 5 (MIR), and 7 (MIR), the overall classification accuracy increased an average of 9%. Results from an increased quantization level (6-bit to 8-bit) provided a smaller increase in overall accuracy - an average of 5%. The difference in classification accuracy for spatial resolution was significant, but in contrast to the other sensor parameters, the finer spatial resolution (30m) resulted in a decrease of classification accuracy - an average of 6% lower.

DeGloria (1984) evaluated the performance of both TM and MSS sensors through the analysis of image and digital data simultaneously acquired over agricultural (December) and forestry (August) study sites in California. Significant results include: (1) the overall spectral, spatial, and radiometric quality of the TM data are excellent; (2) discrimination of crop types on single-date image data is significantly improved by the addition of the first middle infrared band (TM5); (3) the thermal infrared data (TM6) increases the potential for discrimination of agricultural and forestry cover types; and (4) the higher TM spatial resolution (30m versus 79m) increases the ability to discriminate small agricultural fields and boundaries, forest stand boundary conditions, road and stream networks, and small clearings resulting from various forest management practices.

In a related study, Benson and DeGloria (1986) reported TM versus MSS classification accuracies for a forest data set of northern California using traditional interpretation of hard-copy digital image products. The classes included in this study were high density conifer, hardwoods/conifer, hardwood, brush, meadow, grassland, bareground, and rock. Overall classification results varied with sensor and band combination. General results are as follows: High density conifer - TM ranged from 62-85% correct, MSS 80%; hardwood/conifer - TM ranged from 23-57% correct, MSS 47%; brush - TM ranged from 22-80% correct, MSS 20% correct; low density conifers - TM ranged from 50-77% correct, MSS 90%; hardwood - TM ranged from 20-37% correct, MSS 40%; and finally, grassland - TM ranged from 60-67% correct, MSS 43%. There was no statistically significant difference between the TM and MSS classification accuracies reported for the hardwood and grassland categories.

From satellite data obtained over a forested scene in North Carolina, Williams and Nelson (1986) investigated the potential utility of Landsat TM data for forest resource mapping relative to capabilities afforded by MSS data. The seven classes (Level III) were: clearcut, regeneration/pine, pine 1-5 years old, pine 6-10 years old, pine 11-25 years old, mature pine greater than 25 years old, mixed pine/hardwoods, and hardwoods. MSS classification results varied from 2% correct for mixed pine/hardwood, 43% for mature pine, 84% for clearcut, with an overall accuracy of 39%. TM classifications ranged from 39% correct for mixed pine/hardwood, 43% for mature pine, 95% for clearcut, with and overall accuracy of 60%. This is a 20% increase in overall accuracy for TM relative to MSS results. When these seven Level III classes were aggregated into four broad Level II classes (clearcut, young pine, mature pine, hardwood), the results for the two sensors became quite similar. MSS results for the four classes ranged from 48-83% correct, with an overall accuracy of 71%. TM results ranged from 59-95% correct, with an overall accuracy of 77%.

More studies need to be conducted that investigate the classification accuracies of coincident TM and MSS data sets before universal statements can be made on the superior nature of the TM sensor. It is also evident that research is lacking in areas of the Midwestern U.S. concerning the use of TM, and other advanced sensors, such as SPOT.

2.8. Other Effects on Classification Accuracy

2.8.1. Accuracy of Reference Data

The remote sensing researcher almost always requires the use of reference (field-check) data about the resource under investigation (e.g., soil survey maps, forest inventory statistics). Reference data might be used to calibrate a sensor, assist in analysis and interpretation, or verify information extracted from remote sensing data. Clearly, the type of reference data needed depends on the objectives of the project.

Oftentimes, reference data are referred to as "ground truth". This term should be avoided since several studies have shown that "ground truth" may actually be incorrect, or less accurate data than remote images (Smedes, 1975; Curran and Williamson, 1985). "Generally for those classes that can be distinquished from one another by...remote sensing attributes, the remote sensing map is more accurate than the ground truth map (Smedes, 1975)." "Sometimes errors in data collection have caused 'ground truth' actually to be the incorrect data; similarly there are often so many variables involved that one wonders what the 'truth' of the situation really is! (Hoffer, 1978)".

2.8.2. Registration

Registration is the term used to refer to the process of geometrically aligning two or more sets of image data such that resolution cells for a single ground area can be digitally or visually superimposed. Data being registered may be of the same type, from different kinds of sensors, or collected at different times.

To register any two sets of data, ground control points (GCP) must be obtained. GCP's represent the same location in the two or more data sets. Preferably these points are uniquely identifiable (e.g., road intersections, buildings etc.). One map or image must serve as a base and the second map or image will be registered to the first.

Coefficients for the transformation matrix are computed from a set of GCP's which are taken from both sources of data. The output is a matrix of six coefficients:

$$\begin{matrix} a1 & a2 & a3 \\ b1 & b2 & b3 \end{matrix}$$

These coefficients are used to convert base map/image coordinates to the coordinates of the image to be registered. Least squares regression is used to determine an optimal set of coefficients using the following equations:

$$x\ pixel = b1 + (b2 * Xmap) + (b3 * Ymap) \qquad [4]$$
$$y\ pixel = a1 + (a2 * Xmap) + (a3 * Ymap) \qquad [5]$$

where,

map = X,Y coordinates of the base map or image;
pixel = new x,y coordinates computed from Xmap and Ymap for the map or image to be registered.

Then, the program computes the root mean square (RMS) error for each ground control point as below:

$$RMS = (x\ pixel - x\ orig) + (y\ pixel - y\ orig) \quad [6]$$

where,

pixel = new x,y coordinates computed from Xmap and Ymap for the map or image to be registered;

orig = original X,Y coordinates obtained from the map or image to be registered.

The analyst then enters an RMS error tolerance. This tolerance should normally be in the range of 1.0 to 1.5 cells (or pixels).

Most image processing analysis using multiresource data sets is conducted under the assumption that the images are properly registered to one another. Misregistration is a particularly serious problem for field boundaries, where additional pixels will be misclassified due to the mixture of materials in the pixels (Billingsley, 1982). In reality, if the area being analyzed has many small, irregularly shaped fields, then the probability of correctly classifying these fields is low to begin with (using maximum likelihood algorithms); as compared to the probability of correct classification with large, homogeneous fields. With misregistration, the probability of correct classification of small, irregular fields is even lower. Such is often the case with forestry test sites (especially in the Lake States), where stands are small and irregular, and ground control points are difficult to locate.

2.8.3. Mixed (Boundary) Pixel Problem

Mixed or boundary pixels are inherent in any remote sensing scene. Boundary pixels contain a mixed spectral response from two or more adjacent cover classes. Not only may a mixed or boundary pixel be allocated to one or the other classes on either side of the boundary, but it may even be assigned to a third completely different category. Spatial resolution, field size and shape, and registration all effect the frequency of occurrence of mixed or boundary pixels. As mentioned in earlier sections, boundary pixels occur more frequently with coarser resolutions, small and irregularly shaped fields, and with any misregistration problem (Figures 3 and 9). Boundary pixels are inherently more likely to be misclassified. Therefore, a complex scene is more likely to have lower classification accuracies. There are also cases where the pixel is a true mixture of two cover types, yet is not a boundary pixel.

2.9. Discrete Multivariate Analysis

Discrete multivariate analysis techniques were used in this study as a method of accuracy assessment. Classifications resulting from

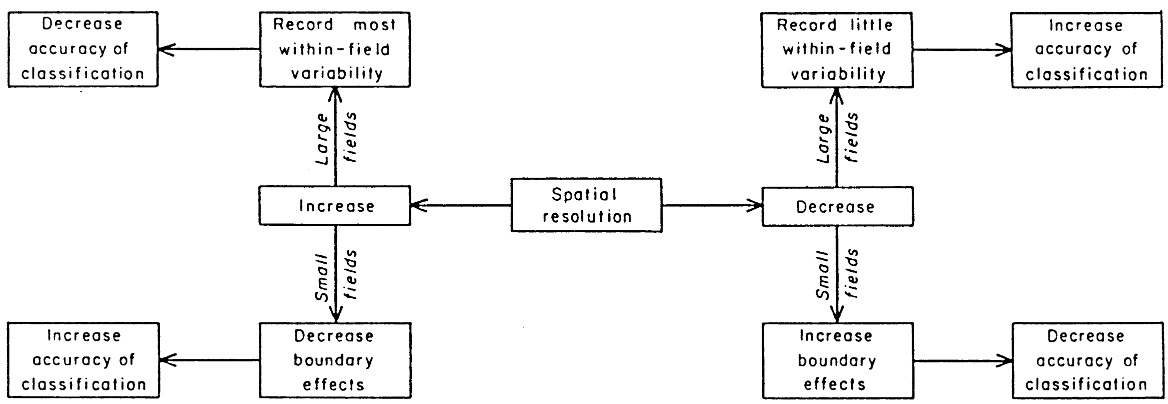

Figure 9. Diagram illustrating the factors affecting mixed or boundary pixels.

satellite analysis are discrete data (e.g., results fall into a particular cover class or they do not), therefore, this type of statistical analysis is most appropriate. "Most previous accuracy assessment techniques have used parametric statistical techniques which assume continuous data and normal distributions" (Congalton et al., 1983).

A contingency table or error matrix is the most common way to represent the accuracy of a Landsat classification. An error matrix is a square array of numbers set out in columns and rows. The numbers in each cell are the number of pixels assigned to a particular cover type relative to the actual cover type as verified from reference data. The columns generally are the reference data (e.g., vegetation map of Itasca Park), and the rows are the computer-assigned categories (e.g., Landsat classification results from the various trials).

Errors of omission (exclusion errors) and errors of commission (inclusion errors) can be evaluated effectively in this manner. A perfect classification would result when all of the off-diagonal cells of the error matrix are zero, meaning that no pixel was misclassified. Because the values on the major diagonal represent the correctly classified pixels, these values are summed up and divided by the total number of pixels, which represents overall accuracy. This measure of overall accuracy performance of an error matrix is the most common use in satellite data accuracy assessment (Table 2).

Table 2. Conventional error matrix to assess Landsat accuracy performance.

Photo/Ground Classes	Landsat Classes			Total Poss	Error (%)*		Mapping** Accuracy (%)
	Aspen	Pine	Other		Omis	Comm	
Aspen	25	5	13	43	42	16	50
Pine	2	50	11	63	21	17	68
Other	5	6	167	178	6	14	83
Total	32	61	191	284			

Overall Landsat Classification Accuracy $= \frac{25+50+167}{284} = 85\%$

*Error:

Pixels of X omission = All other classes in X row
Pixels of X commission = All other classes in X column

**Mapping Accuracy for any class X:

$$\frac{\text{Pixels of X correct}}{\text{Pixels X correct + Pixels X omission + Pixels X commission}}$$

Analysis of variance and discrete multivariate analysis have been used more recently to further assess satellite classification accuracy. ANOVA uses only the diagonal elements in the error matrix; assumes that each cell will be normally distributed (although each cell is actually binomially distributed); and assumes that each category in the error matrix is independent (Rosenfield, 1982). Although the normal distribution assumptions can be corrected using various transformations, rarely are remotely-sensed classes independent.

Discrete multivariate analysis techniques, on the other hand, were designed to handle categorical data. This statistical analysis does not require any transformations of the data, nor assume that the categories are independent. In addition, the entire error matrix is used rather than just the diagonal cells (Congalton et al., 1983). For further reading on discrete multivariate analysis techniques, the reader is advised to consult Fienburg (1983) and Bishop et al. (1975).

In summary, a review of the literature indicates that there are gaps in our knowledge regarding: (1) The use of Landsat Thematic Mapper data for forest-cover-type classification, especially in Minnesota; (2) How the classification accuracy associated with the Thematic Mapper sensor compares quantitatively with coincident Multispectral Scanner data; (3) What are the optimum band/date combinations for the highest overall accuracy, and for certain target species (e.g., Aspen/Birch); (4) Will certain state-of-the-art techniques used to obtain higher classification accuracies for agricultural crops achieve the same results when used for forest classification; and finally, (5) if classification accuracies are reasonably high, is this level of image processing and vegetation classification feasible on a microcomputer for management-level purposes? The present study has been undertaken to answer some of these questions.

3. CONDUCT OF STUDY

3.1. Study Area Description

The study area is Itasca State Park, approximately 12,950 hectares (32,000 acres), located in noth-central Minnesota (Figure 10). The area is glaciated and the park itself is situated on the Itasca Moraine. Knob and kettle topography is characteristic. Numerous lakes and depressions dot the landscape. The upland soils are generally well to somewhat excessively drained (Arneman, 1963; Cummins and Grigal, 1981).

Under the Society of American Forester's Classification System, the major forest types in Itasca State Park are considered part of the western portion of the Northern Forest Region of the Eastern Forest Cover Types (Eyre, 1980). The variable topography, soils, drainage patterns, land use, and fire history account for the considerable variation of plant communities that exist within the park.

While the park vegetation is commonly considered "virgin," only about one fourth of the total area contains partial or full stocking of old growth pine (Hansen et al., 1974). Much of the old-growth pine was either logged and/or frequently burned, and did not regenerate before the park was created. The major forest cover types include: quaking and bigtooth aspen (*Populus tremuloides* and *P. grandidentata*) and paper birch (*Betula papyrifera*) which are widespread on many burned and cut-over areas; mature red pine (*Pinus resinosa*) which can occur in pure stands, but often with a mixture of eastern white and jack pine (*Pinus strobus*, and *P. banksiana*) on the coarser-textured soils; patches of

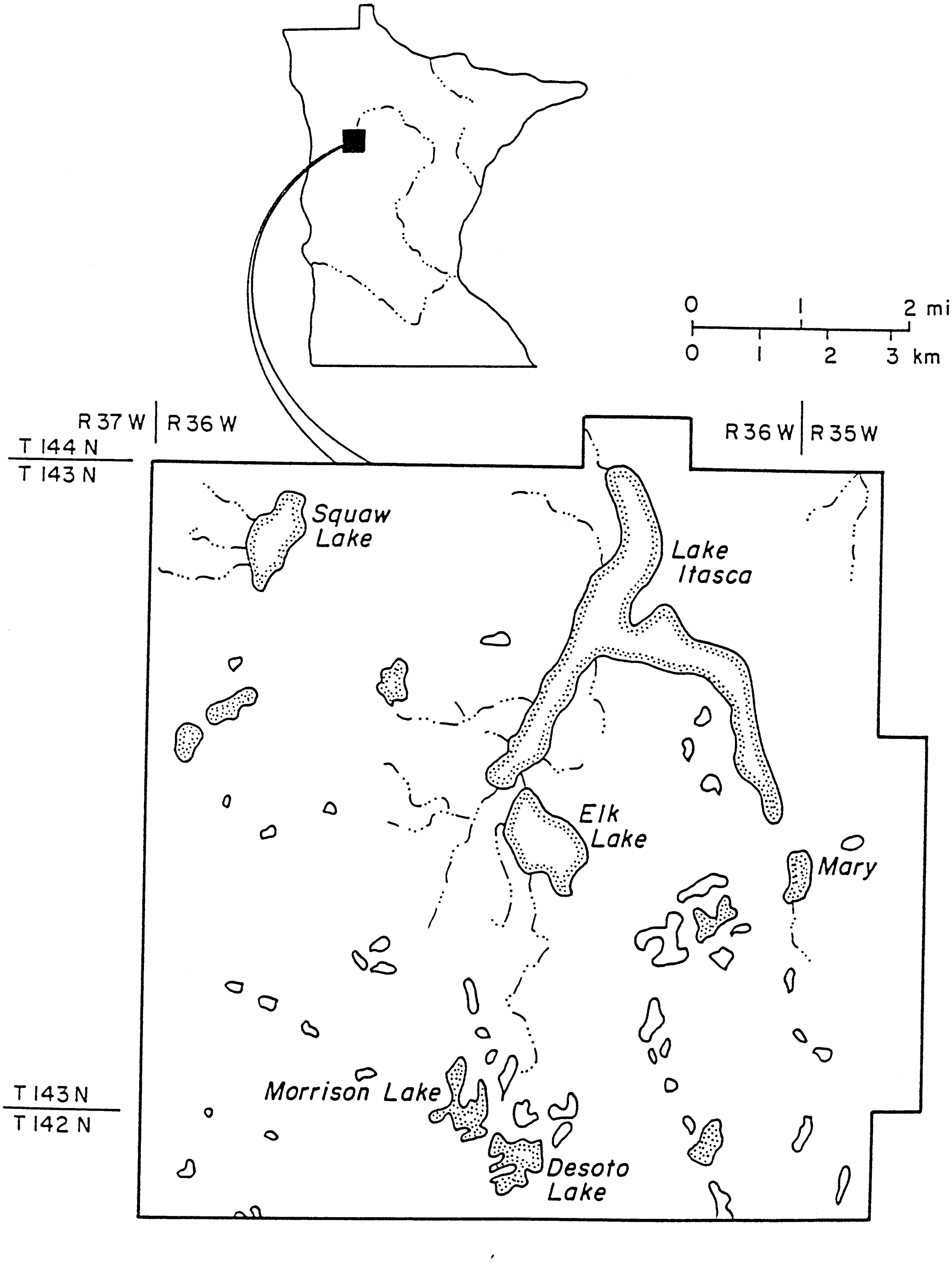

Figure 10. Location of study area, Itasca State Park, in north-central Minnesota.

northern (upland) hardwoods, on the more mesic sites, and a mixture of sugar maple (Acer saccharum), American basswood (Tilia americana), northern red oak (Quercus rubra), and minor species of aspen, birch, bur oak (Quercus macrocarpa), American elm (Ulmus americana), ironwood (Ostrya virginiana), and ash (Fraxinus spp.). Other upland yet mesic conifer species, occurring primarily along lake margins and various drainages, include balsam fir (Abies balsamea) and white spruce (Picea glauca). Lowland conifers include black spruce (Picea mariana) and tamarack (Larix laricina).

There are several cut-over areas (of varying ages) where the old growth aspen was removed and attempts are being made to regenerate red pine. Sedge (Carex spp.) marshes, bogs (Sphagnum spp.), and lowland shrub communities of primarily alder (Alnus spp.) and willow (Salix spp.) are quite common and are scattered throughout the park. Table 3 presents the approximate proportions that each major cover type occupies in Itasca Park. Botanical nomenclature of tree species follows Little (1953).

Itasca State Park was choosen as the study area for many reasons. The three major reasons are: (1) since this was to be an intensive study, an area was needed that would not change drastically during the image-analysis process (e.g., no extensive logging etc.); (2) there are extensive reference data available; and (3) it is an area that is familiar and of interest to people from many disciplines.

Table 3. Vegetation cover types in Itasca State Park and surrounding borders.

Cover Type	Approximate Acreages	Total %
Aspen/Birch	12,670	35
Aspen/Northern Hardwood Mix	3,820	11
Red Pine	4,400	12
Jack Pine	1,000	3
Eastern White Pine	830	2
Spruce-Fir	800	2
Northern Hardwoods	2,700*	8
Lowland Hardwoods**	100	0.3
Tamarack	420	1
Black Spruce	320	0.9
Lowland Shrubs	1,480	4
Marsh and Bog	1,870	5
Field and/or Grass	290	0.8
Cutover	1,060	3
Water	4,300	12
Total	36,060 acres***	

* Compared to 1,512 acres reported by Meyer (1966).

** The Lowland Hardwoods cover type was not used in the final analysis due to the small area it occupied.

*** This acreage figure includes some area beyond the border of Itasca Park.

3.2. Reference Data

Accurate, detailed, reference data was an important component of this study. A detailed cover-type map of the park (Meyer, 1966) was available and used extensively. The map was prepared from 1:15,840 B+W infrared aerial photographs, had a 2.5- to 3-acre (1.0 hectare) minimum mapping unit, and included vegetation type (both forest and nonforest), stand size (seedlings to saw logs), and crown closure class (10% to 70%). Although the map was intensively checked and the interpretations were verified on the ground when it was originally made, many things have changed in the park since 1966. Color infrared aerial photography (35 mm) was therefore obtained over the park by the Minnesota Department of Natural Resources in late August, 1985. I used these more recent aerial photographs, a Zoom-Transfer Scope, and some field-checks to update the vegetation types on the map. No attempt was made to update the stand size or crown density classes.

The most obvious changes in the park were the appearance of cutover areas, the break-up of old stands of pine and aspen, and the development of understory trees to codominance or dominance of the stand. For example, in 1966 there were mature stands of aspen (60-70 years old), with an understory of upland hardwood mix. In 1986, however, the aspen trees were dead or dying, and the dominant cover type has become northern hardwoods. The same successional pattern is occurring with stands that had mature jack pine with aspen understories in 1966. The jack pine is dying and aspen is now the major vegetation type (in terms of both crown density and basal area) in the stand.

After the vegetation map had been updated, it was digitized and the data entered into the microcomputer-based ERDAS image processing/ geographic information system, and converted from vector (polygon) to raster (grid) format (Figure 11). Only the vegetation types (both forest and non-forest) and water-bodies were digitized (Table 3), and registered to the Landsat data to provide a digital map for wall-to-wall (pixel by pixel) evaluation of the classification results.

3.3. Landsat Data Description

Several dates of Landsat-5 Multispectral Scanner and Thematic Mapper data were available that included the Itasca State Park area (Table 4).

Table 4. Landsat scene descriptions.

Scene ID	Sensor	Date	Season
50078-16320	MSS,TM	May 18, 1984	Mid-Spring
50350-16345	TM	February 14, 1985	Late-Winter
50446-16343	TM	May 21, 1985	Mid-spring
50494-16342	TM	July 8, 1985	Early summer
50542-16335	TM	August 25, 1985	Late Summer
50574-16333	TM	September 26, 1985	Late Fall

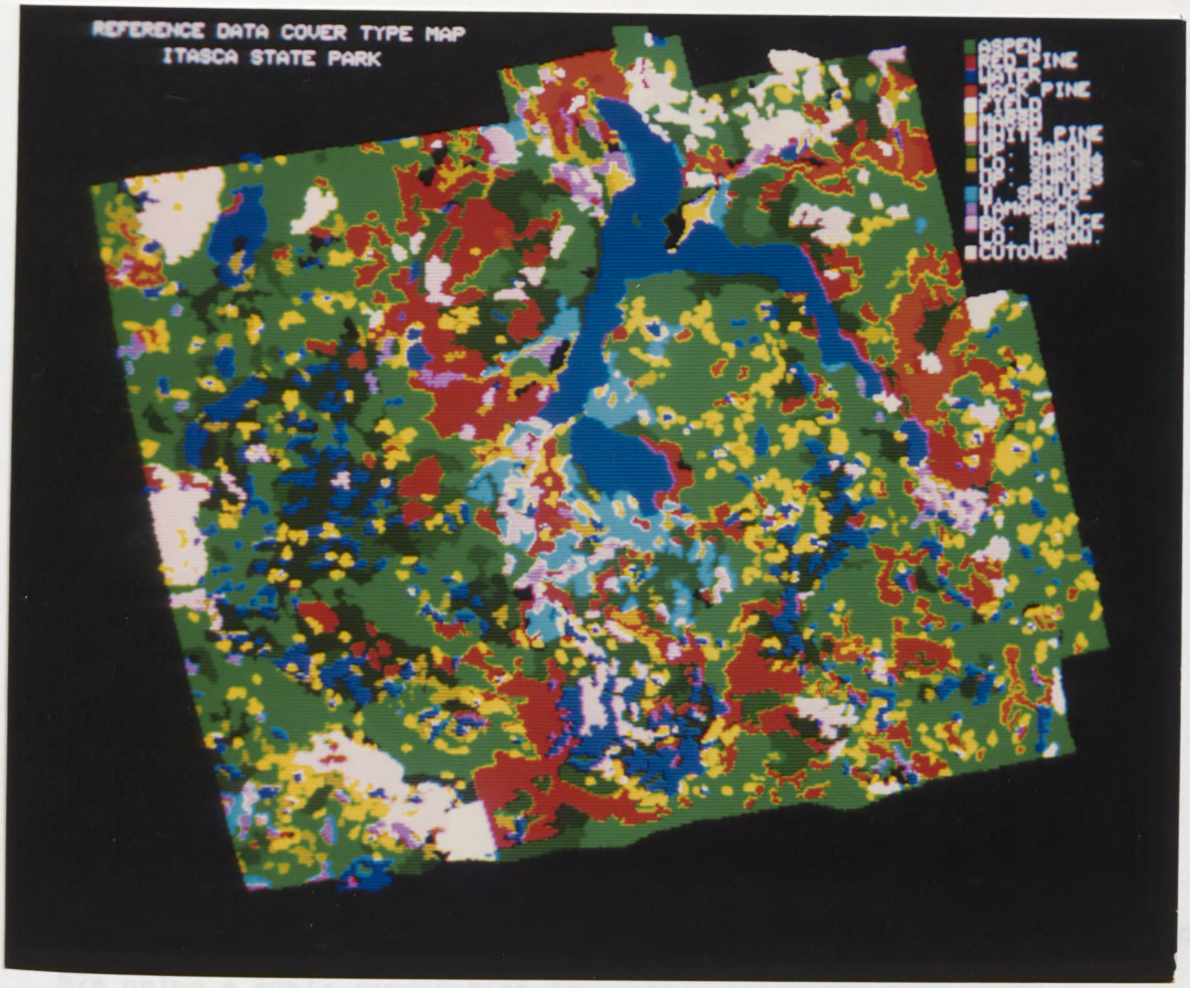

Figure 11. Digitized reference map of Itasca State Park.

The May 18, 1984, date was used for the MSS versus TM coincident data set analysis. The February, May, July, September 1985 data set was used for the optimal spectral band/data combination analysis. The May, July, August, September, 1985 data were used in the greenness, temporal profile part of the study. All imagery were of excellent quality (e.g., no cloud cover, minimal haze, space-craft and sensors operating normally, etc.), except the August 1985 date which had a few scattered clouds but was otherwise good quality.

3.4. Preprocessing of Landsat Data and Design Considerations

3.4.1. MSS versus TM Study

Initially, the subscene of Itasca park and surrounding area was extracted from both the MSS and TM (May 18, 1984) data. The MSS (57m) subscene was 256 x 256 pixels in size, while the TM (30m) equivalent was 512 x 512 pixels (Figure 12). The TM data were then degraded to approximate MSS spectral and spatial characteristics. MSS spectral simulation was achieved by simply using TM bands 2,3,4 which are the best available wave band combinations for approximating the MSS bands 1,2,3,4 (see Table 1, and Crist and Cicone, 1984a). An approximation of MSS spatial resolution was achieved by degrading the TM 30m data to 57m using a cubic convolution (geometric correction) resampling program. The TM data was degraded to 57m rather than 79m for the following reason: (1) the MSS data has a 57m along-scan sampling rate; (2) the MSS data is preprocessed and resampled by NASA to 57 x 79m pixel size before we receive it. Although the size of each pixel is

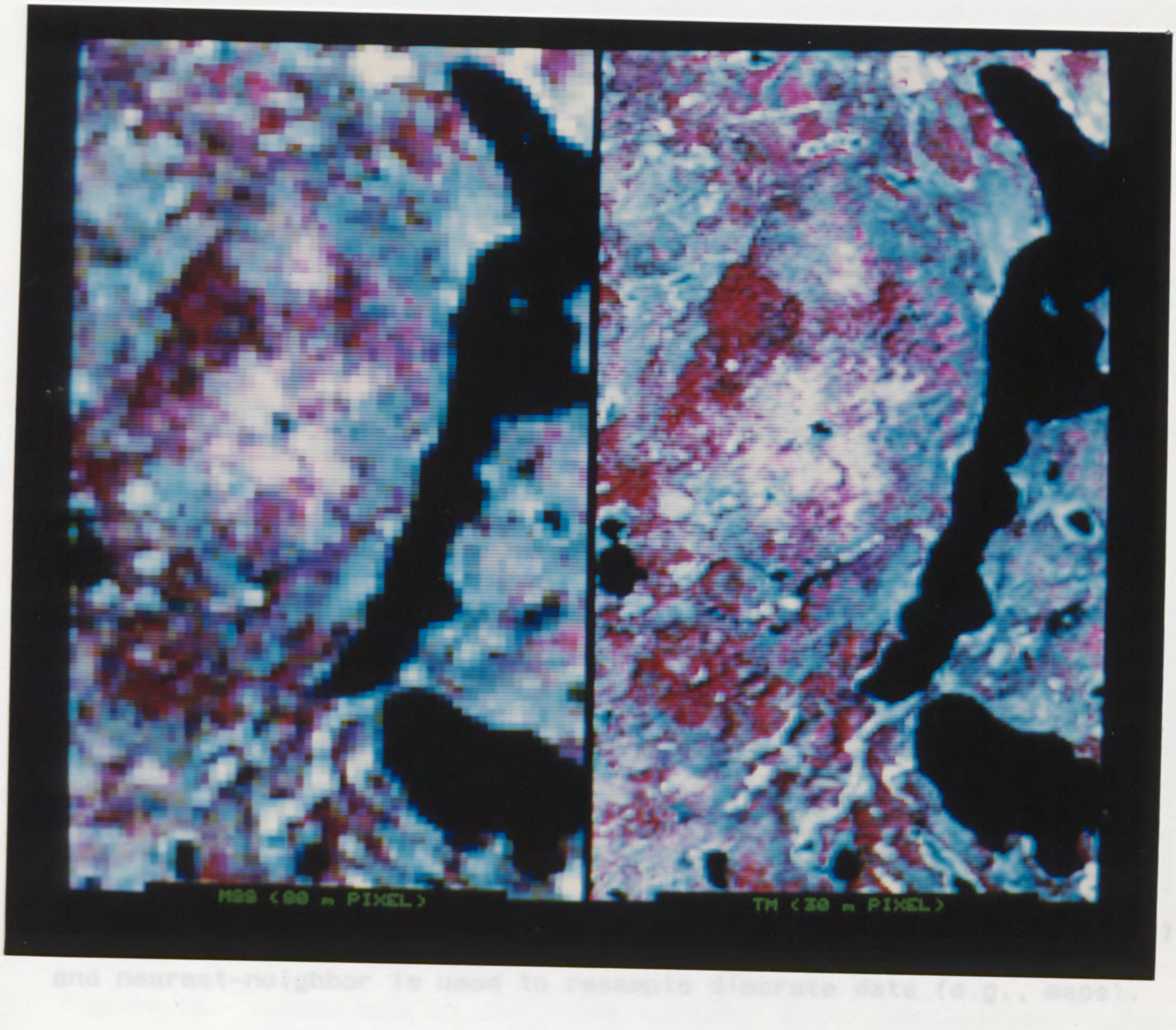

Figure 12. Near infrared composite comparison of MSS 57m and TM 30m data from a portion of Itasca State Park.

57m, the MSS IFOV is still only 79m. I simulated the 57m-by-57m pixel format, rather than trying to simulate the 79m IFOV of MSS data. Table 5 shows the design that results from these preprocessing steps.

Table 5. Landsat MSS and TM spatial and spectral characteristics compared statistically for performance in forest classification.

Sensor	Pixel Size (m)	Spectral Bands
MSS	57	1,2,3,4
TM	57	2,3,4
TM	57	1-6
TM	30	1-6
TM	30	2,3,4

By comparing results obtained from this data set, we can determine if it is the spatial (Figure 12) or spectral resolution (Figure 13) that differences in classification results can be attributed.

The vegetation map was then rectified and registered to the Landsat data (both the 57m and 30m data sets) to within 1.0 to 1.5 pixels RMS error, using a nearest-neighbor resampling program. The difference between the resampling programs is that cubic convolution (mentioned earlier) is used to resample continuous data (e.g., images), and nearest-neighbor is used to resample discrete data (e.g., maps).

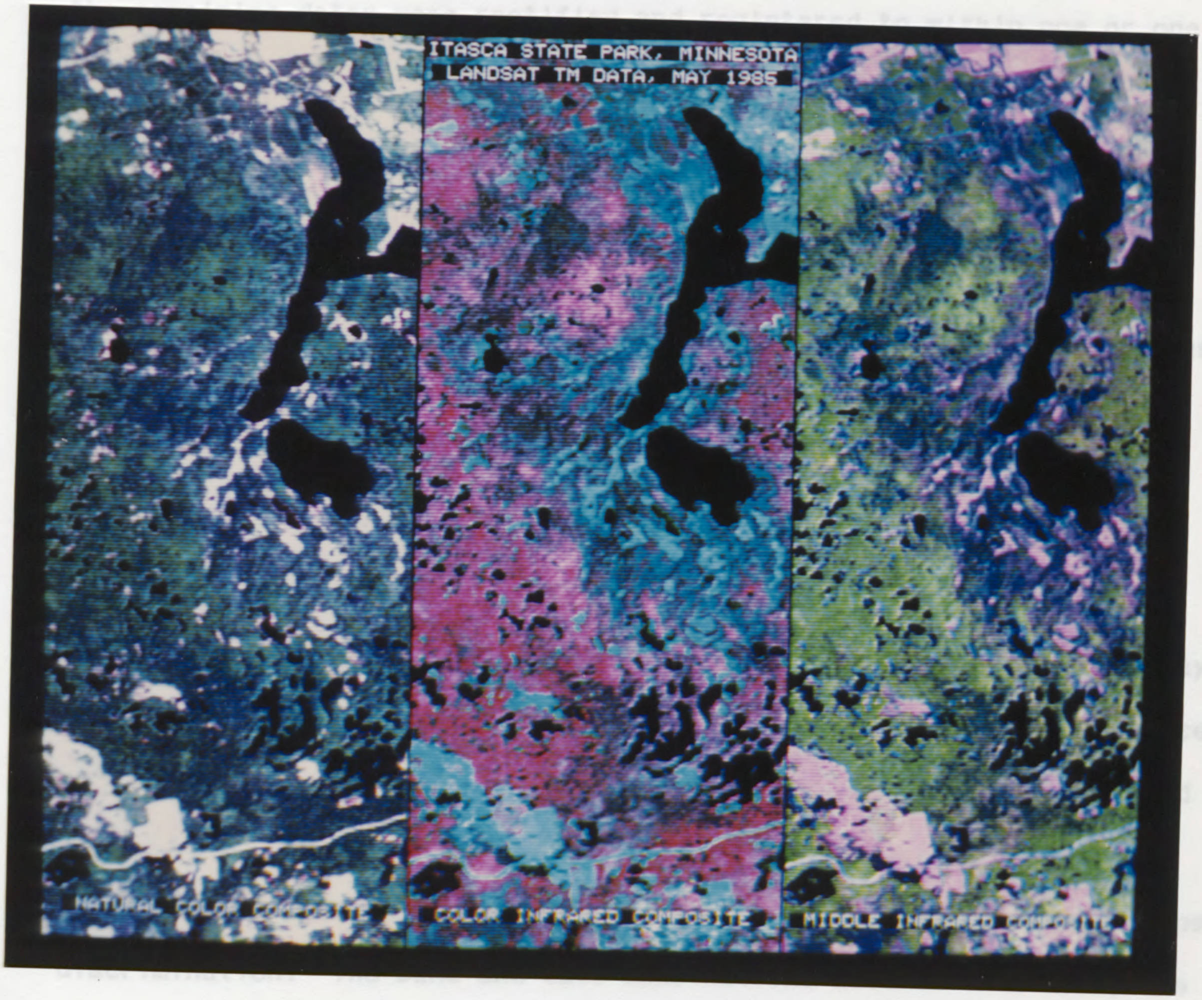

Figure 13. Comparison of different spectral band combinations (normal color - bands 1,2,3; near infrared - bands 2,3,4; middle infrared - bands 3,4,5) from TM 30m data, May 18, 1984.

3.4.2. Optimal Band/Date Combination Study

Initially, the subscene of Itasca State Park and some surrounding area was extracted from each TM image (February, May, July, September, 1985) (Figure 14). The subscenes were 512 x 512 pixels in size and had seven spectral bands each. Using the May, 1984, TM data as a base, all the remaining dates were rectified and registered to within one or one and one-half pixels RMS error, using the cubic convolution resampling program. The vegetation map was also rectified and registered to all four dates to within one or one and one-half pixels RMS error, using the nearest-neighbor resampling program. With these preprocessing steps complete, the Landsat images could be analyzed individually or as a multitemporal data set; and compared on a pixel-by-pixel basis with the reference (vegetation) map.

As mentioned in the literature review section, it is often unnecessary and practically impossible to examine all combinations of spectral bands available in a multitemporal data set. An objective way of determining a subset of bands to use is a divergence measure. Since the ERDAS does not currently have such a measure available, I selected the bands from the current literature that were reported as yielding the highest classification accuracies for overall vegetation cover type discrimination. The band and date combinations used in this study are listed in Table 6.

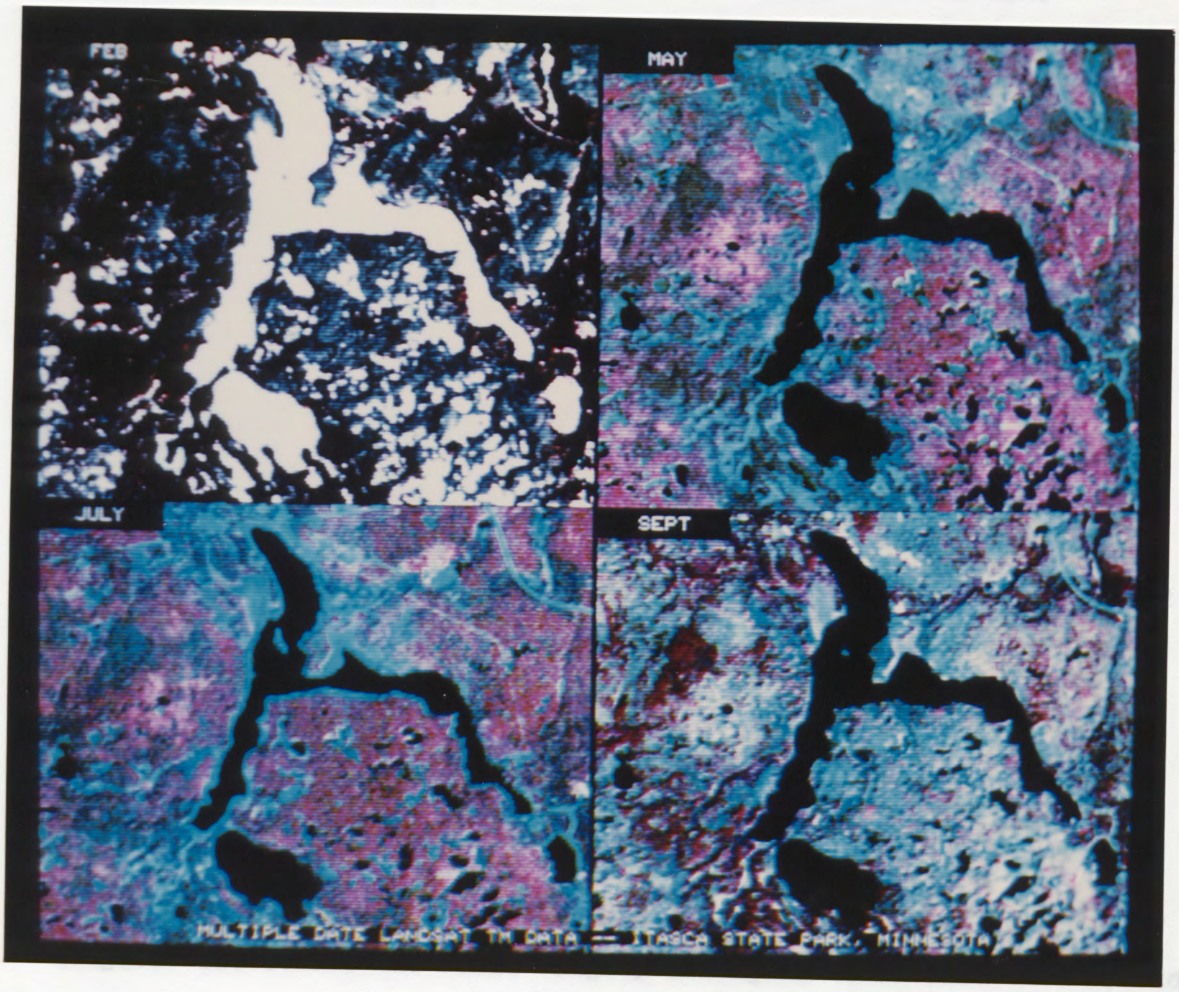

Figure 14. Near infrared composite of each date (February, May, July, September, 1985) used in the band/date combination study of Itasca State Park.

Table 6. Landsat-5 Thematic Mapper band and date combinations used for vegetation type classification of Itasca State Park.

Date	Band Combinations
Single Dates	1,4,5 3,4,5 1,3,4,5 1,2,3,4,5,7 1-7
Multitemporal Dates	4 4,5 Greenness

3.4.3. Greenness and Temporal Profile Study

As mentioned in previous sections, the Itasca Park subscene (512 x 512 pixels) was extracted from each TM image (May, July, August, September 1985) rectified and registered to one another. The dimensionally of the data was then reduced by using a linear transformation - the TM Tasseled Cap transformation (or Greenness-Brightness). Brightness, the first feature of the transformation, is a weighted sum of all the bands roughly analagous to albedo. The second feature, Greenness, is a linear combination of the difference between the near infrared bands and the visible bands. Targets with high densities of green vegetation should produce high greenness values. Thus, greenness, the feature of primary interest in this study, is obtained by multiplying each pixel in the six reflective bands of each date (May, July, August, September, 1985) by the following coefficients (Crist and Cicone, 1984a):

	TM Band					
Feature	1	2	3	4	5	7
Greenness	-.2848	-.2435	-.5436	.7243	.0840	-.1800

The greenness images of the four dates were combined (Figure 15) and analyzed as if they were one image with four bands.

The temporal-profile model is an attempt to model the time behavior of spectral response for various cover types, and use these varying responses over time to discriminate between cover types (see section 2.6.3.). To estimate the parameters for this model from Landsat data, preprocessed, multidate data is transformed into greenness-brightness space, then greenness is fitted to the model.

The Remote Sensing Lab provided NASA-Goddard Space Flight Center with a four-date (May, July, August, September 1985) data set of TM data covering Itasca State Park. The NASA-Goddard team used a linear (least squares regression) model to fit the greenness data to the temporal-profile model. This fitting procedure takes several hours on a mainframe computer. A nonlinear fit would have been preferable, but will not be available for some time. The NASA Goddard team returned images of the profile parameters to the Remote Sensing Lab for

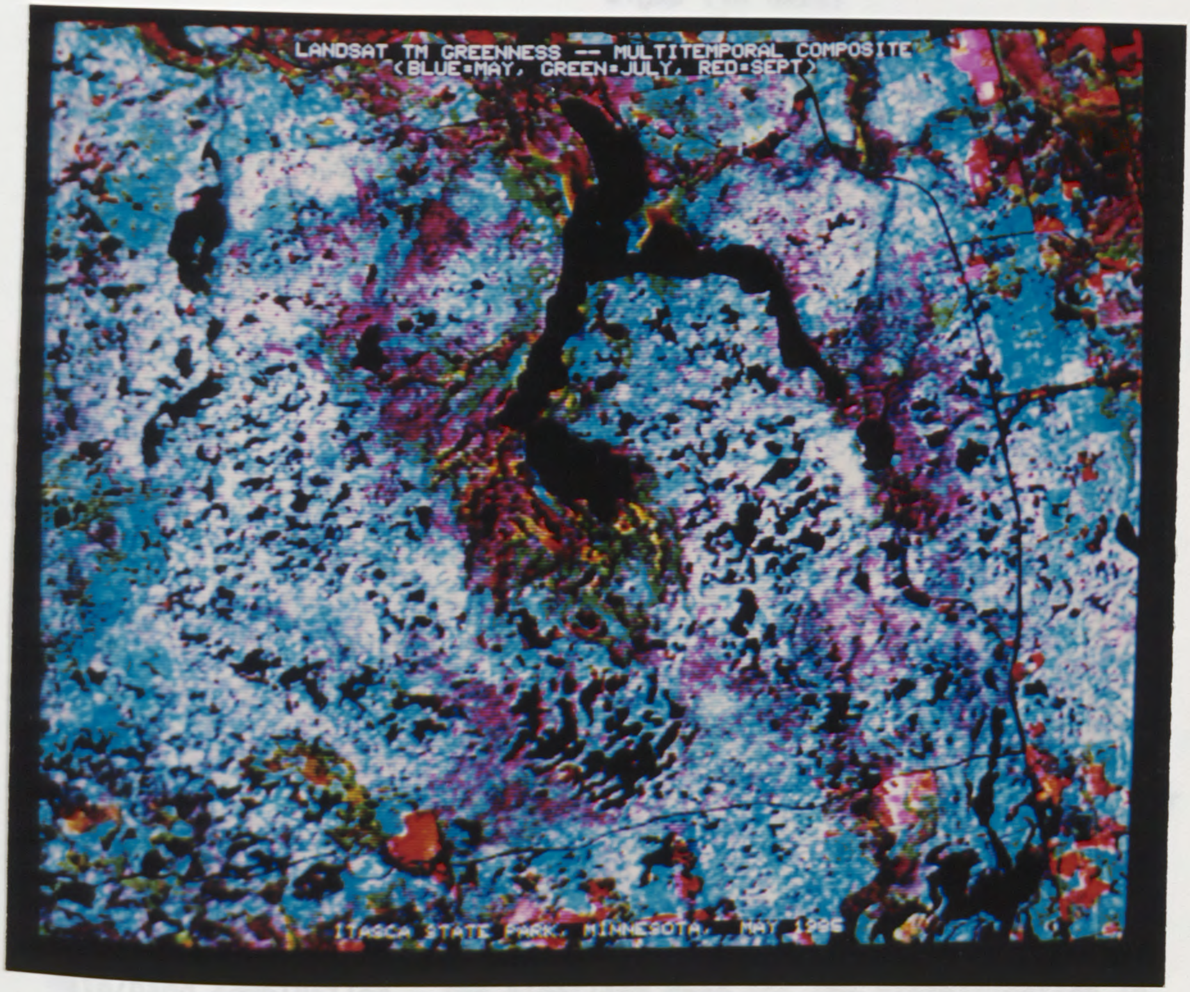

Figure 15. Greenness image of Itasca State Park.

classification of the vegetation types. The parameters (images) analyzed are as follows:

File	Parameter
1	alpha (α)
2	maximum greeness (Gm)
3	time of peak greeness (in day of year)
4	sigma (in days)
5	beta (β)
6	Gm minus Go

Since the parameters Gm, tp and σ account for more than 95% of the information in the original data (Badhwar, 1985), these features were classified. A second classification used all six of the profile parameters to determine whether the other parameters might contain additional information.

3.5. Training and Classification

The supervised training and classification approach was used exclusively in the study. Statistics (training field samples) were collected, checked for normality, and verified according to the reference data. The location of the training samples was the same for all date/band/study combinations for both MSS and TM data. The training statistics, however, were independently generated for each date/band combination. The algorithm used for the classification in all cases is the Gaussian Maximum Likelihood. A classification map and tabular results are the final products of the image processing analysis.

The classification maps were subjected to two operations before they were directly compared to the reference data. Thresholding was used to screen out poorly classified points. I set a threshold value of 10% for each class in each classification map. This 10% value means that any point having a probability of occurance of less than 10% correct will be screened out and not used in the final analysis (i.e., becomes part of a null or not classified class).

The second operation performed on each classification map was filtering, which simply serves to "level out" minor fluctuations in the data. Each pixel in the Landsat classification map is equal to approximately one-quarter acre if it is 30m TM data, or one acre if it is 57m MSS or degraded TM data. The minimum mapping unit on the reference map is 2.5-3 acres (1.0 hectare). This creates a problem. If the satellite detected a small pocket of vegetation within a bigger stand, and the results are directly compared with the reference data, the conclusion would be that the satellite classification was wrong (even if it were not). Therefore, all of the TM and MSS classification maps were filtered to create 2.5-3 acre (1.0 hectare) minimum units equivalent to the reference map.

3.6. Measures of Classification Performance

Classification performance was evaluated for all cover types by two categories of performance measures: (1) pixel by pixel (wall-to-wall) accuracy, obtained by comparing Landsat classifications of all pixels (redefined to a 2.5-to 3-acre minimum) to the reference map of Itasca Park; and (2) test field accuracy, obtained by comparing test field (pure, stand center pixels) classifications to the reference map.

The test fields were created by using a set of successively increasing filters on the class boundaries of the reference map. The boundary filter creates a file containing outlines of edges between the class areas, then the analyst sets these boundary values equal to zero. Zero values are then excluded from the analysis. Three sizes of filters were used: 2 x 2, 3 x 3, 4 x 4 pixels. The 2 x 2 filter eliminates problems of misclassification due to misregistration and some boundary pixels. The 3 x 3 filter eliminates more problems of misclassification due to boundary pixels, and eliminates stands or vegetation types covering small or linear areas. The 4 x 4 boundary filter eliminated all but the most pure areas of the larger polygons. These pure areas are called "test field" in this study (Figure 16). Most Landsat studies use such pure areas to determine their classification results for what are often called "test fields". The per pixel (wall-to-wall) classification may bias the classification accuracies downward due to misregistration etc., while the "test field" or "test area" approach biases the classification accuracies upward due to its pureness.

The highly variable and mixed vegetation of Itasca Park necessitated the aggregation of the original 14 Level III classes into 10 Level III, and 7 and 4 Level II classes to determine the effect on

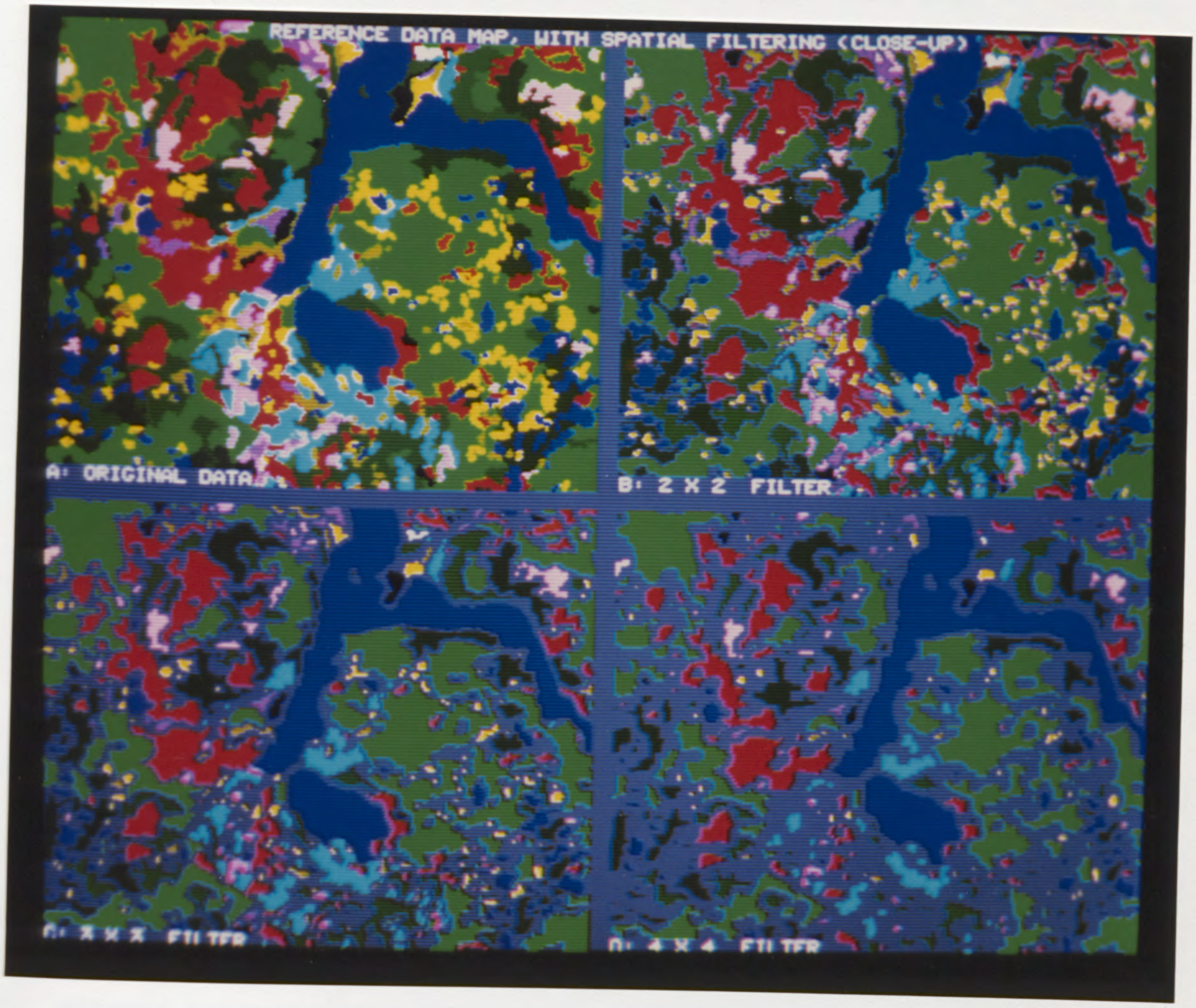

Figure 16. Reference vegetation map of Itasca State Park demonstrating the effect of using successively larger boundary filters. Note the pure "test fields" that result from using a 4x4 boundary filter.

Table 7. Resource classes used in this study - fourteen Level III classes aggregated down to four Level II classes.

14 Classes	10 Classes	7 Classes	4 Classes
Aspen/Birch	Aspen/Birch	Upland Hardwoods	Hardwoods
Aspen/No. Hdwd Mix	Red Pine	Upland Conifers	Conifers
Red Pine	Jack/White Pine	Lowland Conifers	Water
Jack Pine	Spruce-Fir	Field and/or Grass	Other
White Pine	No. Hardwoods	Marsh/Bog/L. Shrub	
Spruce-Fir	Tamarack/B. Spruce	Cutover	
No. Hardwoods	Field and/or Grass	Water	
Tamarack	Marsh/Bog/L. Shrub		
Black Spruce	Cutover		
Lowland Shrubs	Water		
Marsh and Bog			
Field and/or Grass			
Cutover			
Water			

classification accuracy. Table 7 lists the various and original and aggregated classes.

3.7. Statistical Evaluation of Results

Discrete multivariate analysis techniques were used in this study as a method of accuracy assessment. Two different methods were used in this study: (1) a process called normalization, and (2) a measure of agreement between error matrices. (i.e., $\hat{K}$).

The normalization process allows for direct comparison of corresponding cell values in different error matrices (Bishop et al., 1975). "Iterative proportional fitting" converges to a unique set of maximum-likihood estimates and is the procedure (algorithm) used to normalize the error matrix. The rows and columns of the matrix are successively balanced until each row and column adds to a given value - say 1.0. Each cell in the matrix represents both errors of omission and commission. The corresponding cells of two or more error matrices can then be compared without regard for differences in sample size, while incorporating omission and commission errors into the accuracy assessment (Congalton et al., 1983). It is a relative measure of which cell or matrix is "better" because there is no test for significance between corresponding cell values. In this study, sample sizes are not equal between cover types. The aspen cover type, for example, has significantly more pixels in the training sets than does the tamarack cover type. Among the band/date combinations, however, the same cover type (e.g., aspen training sets in February vs. aspen training sets in July) will have the same sample size (same number of pixels).

An assumption using the normalization procedure is that all cells are of equal weight or importance; however, this assumption is not always true using remotely-sensed (or other) data.

The second method of accuracy assessment using discrete multivariate analysis is a method of comparison that tests if the overall agreement in two separate error matrices is significantly different (Bishop et al., 1975). The statistic used for this comparison is called Kappa or KHAT ($\hat{K}$). Each matrix can be tested separately to determine if the agreement between the classification and reference data is significantly different from zero (e.g., determine if the classification is significantly greater than a random assignment of cover types to pixels). A more powerful test, however, is a pairwise test of significance that can be performed between two independent KHAT's using the normal curve deviate to determine if the two error matrices are significantly different (Cohen, 1960; Congalton, 1983). The KHAT statistic is calculated by:

$$\hat{K} = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} * x_{+i})} \qquad [7]$$

where,

r = number of rows in the matrix

x_{ii} = number of observations in row i and column i

x_{i+} = marginal total of row i

x_{+i} = marginal total of column i

N = total number of observations

Confidence intervals can be calculated for KHAT using the approximate large sample variance:

$$\hat{\sigma}(\hat{K}) = \frac{1}{N}\left[\frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2-\theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2(\theta_4-4\theta_2)^2}{(1-\theta_2)^4}\right] \quad [8]$$

where,

$$\theta_1 = \sum_{i=1} \frac{x_{ii}}{N} \qquad \theta_2 = \sum_{i=1} \frac{x_{i+} * x_{+i}}{N^2}$$

$$\theta_3 = \sum_{i=1} \frac{x_{ii}}{N}\left(\frac{x_{i+}}{N} + \frac{x_{+i}}{N}\right) \qquad \theta_4 = \sum_{\substack{i=1\\ j=1}} \frac{x_{ij}}{N}\left(\frac{x_{j+}}{N} + \frac{x_{+i}}{N}\right)^2$$

The test statistic for significant difference in large samples is given by:

$$Z \sim \frac{\hat{K}_1 - \hat{K}_2}{\hat{\sigma}_1^2 + \hat{\sigma}_2^2} \quad [9]$$

The confidence intervals and significance tests are based on the asymptotic normality of the KHAT ($\hat{K}$) statistic.

The error matrices generated from several classifications can now be compared, two at a time, to determine which classifications are significantly better than the rest. The effects of individual factors (e.g., spatial resolution - 30m vs 57m; or May bands 1,3,4,5 vs. September bands 1,3,4,5) on classification accuracy can be tested. The one restriction is that only one factor in the classification can vary at a time and all other factors (e.g., algorithm, analyst, etc.) in the scene, must be held constant. This is a common practice, however, so the technique serves a useful purpose (Congalton, 1983).

4. RESULTS AND DISCUSSION

The focus of this study has been to determine how various forest and satellite sensor characteristics affect the classification accuracies of forest and other vegetation cover types in north-central Minnesota. Major areas of emphasis were: (1) to identify and quantify through statistical analysis whether the limitations in classification accuracy are due to the spectral, spatial, or temporal (or a combination) factors; and (2) to use several new techniques that have proven successful for classifying agronomic crops, yet have not been tested to any large extent on forest types.

4.1. Spectral Response Analysis

The mean spectral responses of selected aggregated, training samples for nine cover type classes of TM data are shown in Figure 17 and Table 8. The responses are similar for the MSS data in the visible and near infrared bands, yet the variances are larger. These statistics show the similarities and differences between selected cover types across the six reflective bands. It should be noted that the responses are relative and since the curves cannot be directly compared to spectral reflective curves the bands are not calibrated the same.

The jack pine cover type, for instance, has a mean spectral response that is similar to red pine in the visible bands (band 1-3), a lower mean spectral response than red pine in the near infrared (band 4), yet a higher response in the first middle infrared band. Jack pine is much darker in tone because of its more compact and conical crowns.

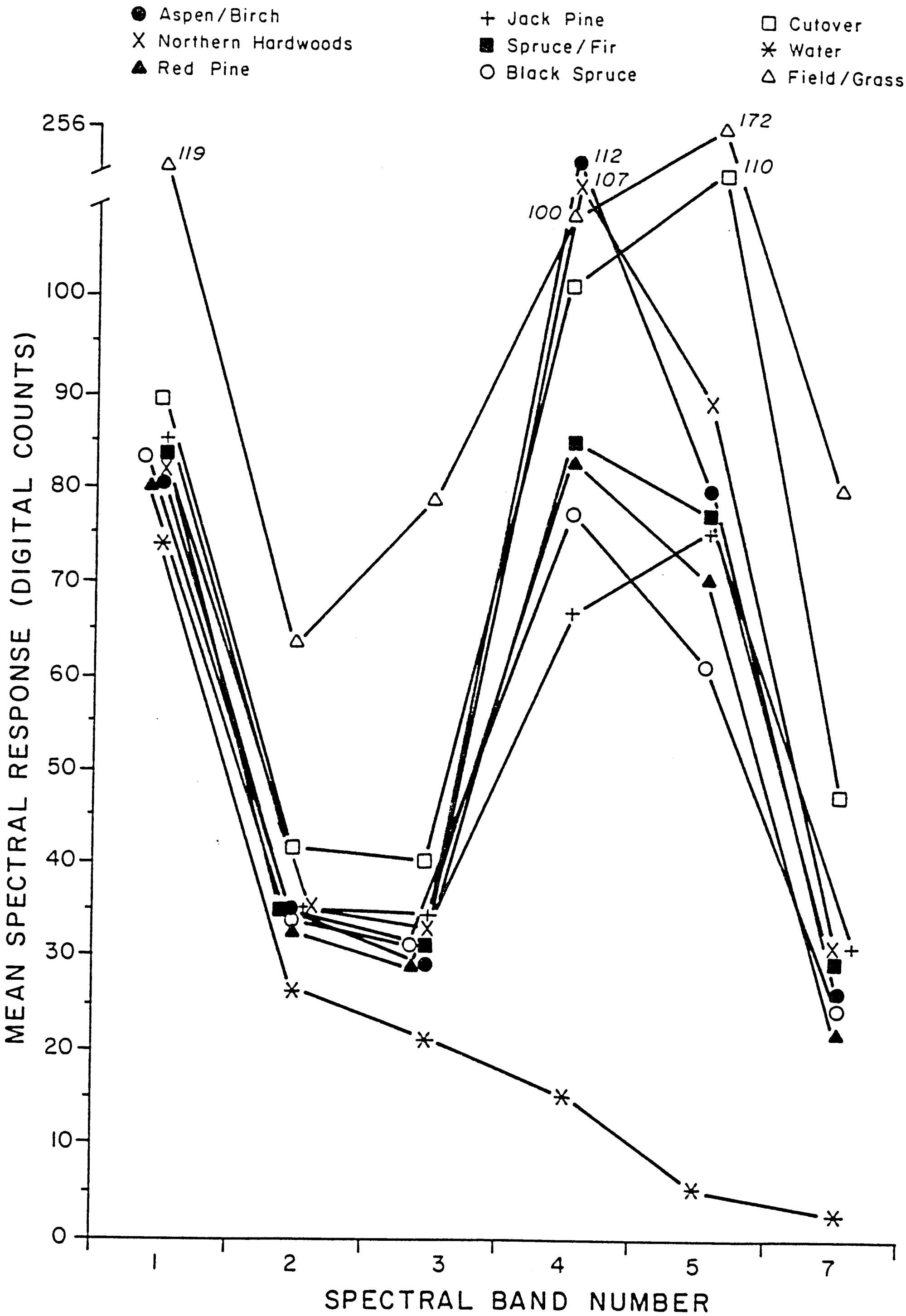

Figure 17. Mean spectral response from aggregated training data for selected cover types using Thematic Mapper data - May 18, 1984.

Table 8. Mean spectral response in digital counts from aggregated training sets for TM Landsat data–May 18, 1984.

	Landsat Band					
Cover Type	1	2	3	4	5	7
Aspen/Birch	75	30	24	112	75	22
No. Hardwoods	76	30	27	107	84	26
Red Pine	75	28	24	78	66	17
Jack Pine	78	30	28	61	72	26
Spruce/Fir	77	30	26	80	73	25
Black Spruce	77	29	26	72	56	19
Cutover	84	36	35	96	110	42
Field/ Grass	119	58	74	100	172	75
Water	69	21	16	10	5	2

The higher response for jack pine in the middle infrared bands suggests a lower moisture content in the needles and background materials, or a lesser overall density of the stands. Black spruce has a darker signature - similar to jack pine in the near infrared, and a much lower response than the other conifers in the first middle infrared band, suggesting higher moisture content, a closed canopy, shadowing, or a combination of these biophysical factors.

As expected, aspen/birch and northern hardwood signatures are similar across all bands. However, there are slight differences in the mean spectral response in the red (band 3), near infrared, and middle infrared bands. This difference in response may be the increased amount of chlorophyll and leaf area index in the aspen, which has leaf-out (May 18) 2-3 weeks ahead of the other hardwoods. The differences between the deciduous and coniferous species are more dramatic than within type differences.

The cutover cover type is higher in mean spectral response across all bands, except in the near infrared. Again, this is to be expected. The cutover areas generally have a cover of upland brush, grass, and various herbaceous species (e.g., bracken fern, rasberries, etc.) There are also some older cutover areas that have a lot of young aspen saplings. In mid-May the dead materials still dominate the spectral response and are higher in reflectance in the visible bands. The near infrared band is not as reflective for the cutover areas as compared to the aspen type. The high response in band 5 may be due to lower moisture or chlorophyll content. The field and/or grass type follows the same pattern as the cutover areas, and though it is much more reflective in all cases.

Figure 17 illustrates two important points about the Itasca Park data set: (1) In order to discriminate between cover types that are very similar, it is very important to choose the appropriate set of bands for the analysis; and (2) the narrower and additional bands (especially band 4 and band 5) of the TM appear to yield more information and to separate cover types to a finer degree.

Canopy closure (and/or density) and age of species also affect the spectral response (Table 9 and Figure 18). Differences are especially noticeable in the middle infrared (bands 5 and 7). Although leaf and soil moisture are said to control reflectance in this portion of the spectrum, recent studies have found that the middle infrared bands are also sensitive to canopy closure, tree age (size), leaf area index and general forest structure (Spanner et al., 1984; Butera, 1986; Peterson et al., 1986; Horler and Ahern, 1986; Badhwar et al., 1986). Horler and Ahern (1986) also indicated that "shadowing is suggested as a factor at least as important as leaf moisture in influencing the spectral reflectance in the middle infrared bands". There is need for further research in this area. Since I did not isolate forest canopy structure factors, I can only suggest that it is not species type alone that is contributing to the response (yielding information) in the middle infrared bands.

Table 9. Mean spectral response of individual training areas for TM Landsat data—May 18, 1984.

Cover Type	Landsat Band 1	2	3	4	5	7
Red pine						
old growth (200+ years)	77	30	25	68	49	17
plantation (30 years)	81	33	28	89	66	25
Red pine						
low density (aspen understory)	81	33	30	72	81	31
Cutover						
new cut (herbaceous)	96	42	48	69	140	64
older cut (young aspen)	85	36	36	75	112	46
Aspen/Birch						
(pure)	80	33	30	80	88	34

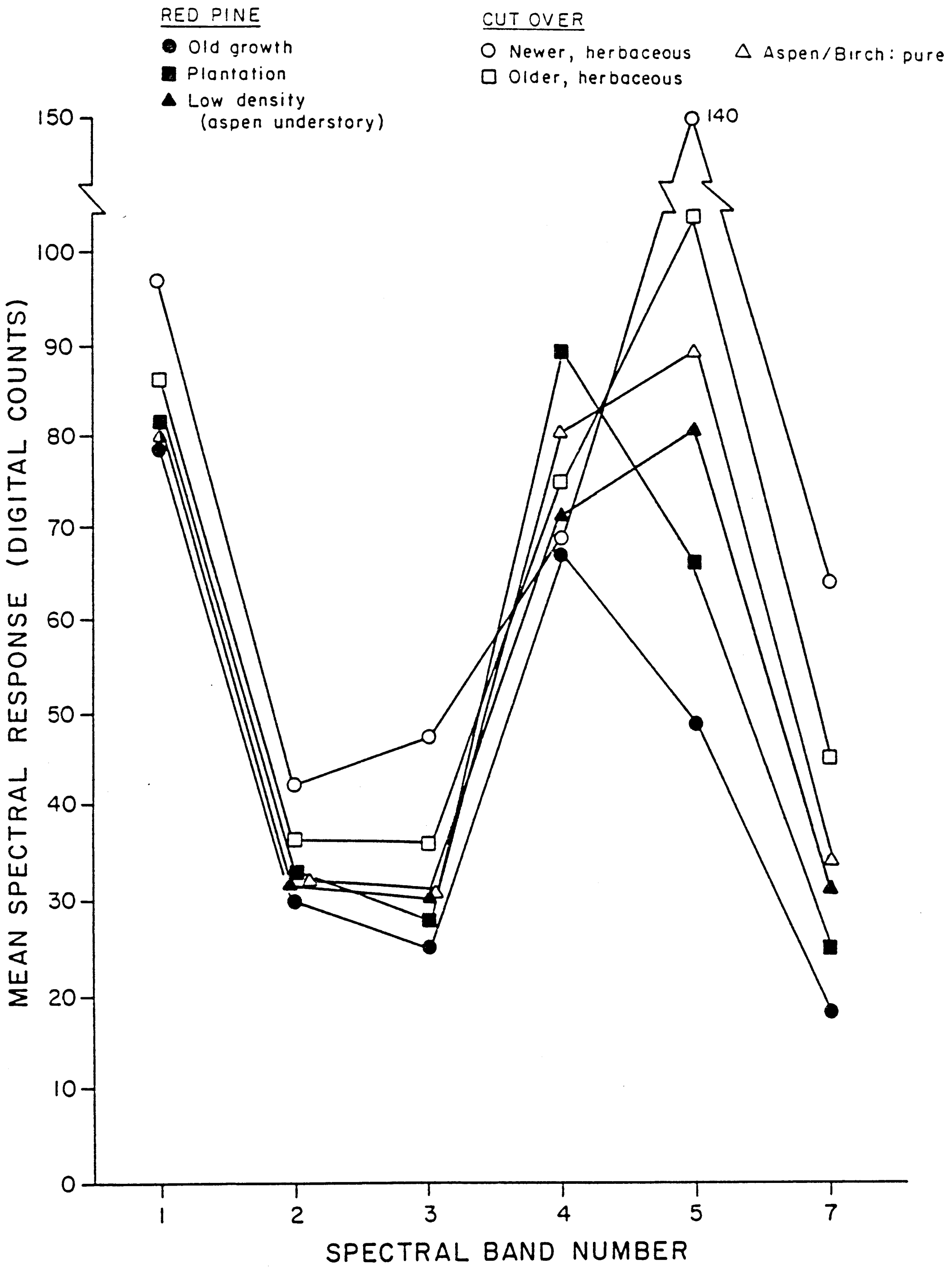

Figure 18. Mean spectral response from individual training samples demonstrating the effect of canopy closure (and/or density) and age of species - TM data May 18, 1984.

4.2. MSS vs. TM Classification Results

Figures 19 and 20 are classification maps from MSS 57m (bands 1-4) and TM 30m (all six reflective bands) data, respectively. Table 10 and Figures 21 and 22 summarize the classification results from this portion of the study. Figure 21 features the traditional overall accuracy data (results from the diagonal of the error matrix without consideration of errors of omission and commission), while Figure 22 features the normalized accuracy data (results from the diagonal that includes both omission and commission errors).

Overall accuracy results indicate that in all cases the TM data performed significantly better than the MSS data. The spatially degraded TM data with the same spectral bands as MSS (TM 57m 2-4), performed only slightly better (anywhere from 0-6% increase) in classification accuracy than the MSS results. The degraded TM data with the additional spectral bands (TM 57m 1-6), however, increased accuracies from 3-9%, indicating that there is some advantage to using all of the spectral bands.

The 30m TM data with bands similar to MSS data (TM 30m 2-4) were not significantly better from the 57m TM 1-6 results, and only slightly higher than the 57m TM 2-4 accuracies. The 30m TM data, with the full complement of reflective bands, had the highest overall accuracies ranging from a 7-15% significant increase over the 57m MSS 1-4 data set.

The normalized accuracy data set (Figure 22) demonstrates similar trends, supporting the hypothesis that the spectral resolution is more

Figure 19. Classification map of Itasca State Park using 57m MSS data and all four bands for seven resource classes – May 18, 1984.

Figure 20. Classification map of Itasca State Park using 30m TM data and all six reflective bands for seven resource classes - May 18, 1984.

Table 10. Percent overall and normalized accuracy performance for MSS versus TM spatial and spectral resolutions for different numbers of classes and per pixel vs. test field measures.

Spatial/Spectral Combination	Accuracy Performance (%) Overall*	Normalized
	14 Classes	
Per Pixel		
MSS 57 (1-4)	37	26
TM 57 (2-4)	40a	29
TM 57 (1-6)	42	34
TM 30 (2-4)	40a	31
TM 30 (1-6)	44	37
Test Fields **		
MSS 57 (1-4)	49	34
TM 57 (2-4)	54	38
TM 57 (1-6)	57b	43
TM 30 (2-4)	58b	44
TM 30 (1-6)	64	50
	10 Classes	
Per Pixel		
MSS 57 (1-4)	40	36
TM 57 (2-4)	42	38
TM 57 (1-6)	46	44
TM 30 (2-4)	43	42
TM 30 (1-6)	48	47
Test Fields		
MSS 57 (1-4)	52	44
TM 57 (2-4)	56	49
TM 57 (1-6)	60c	56
TM 30 (2-4)	60c	58
TM 30 (1-6)	67	65

Table 10 (cont).

Spatial/Spectral Combination	Accuracy Performance (%) Overall	Normalized
	7 Classes	
Per Pixel		
MSS 57 (1-4)	57	49
TM 57 (2-4)	58	51
TM 57 (1-6)	62d	57
TM 30 (2-4)	62d	54
TM 30 (1-6)	66	62
Test Fields		
MSS 57 (1-4)	70	59
TM 57 (2-4)	73	64
TM 57 (1-6)	78	72
TM 30 (2-4)	79	72
TM 30 (1-6)	84	82
	4 Classes	
Per Pixel		
MSS 57 (1-4)	62e	60
TM 57 (2-4)	62e	60
TM 57 (1-6)	65	63
TM 30 (2-4)	67	67
TM 30 (1-6)	69	67
Test Fields		
MSS 57 (1-4)	73	74
TM 57 (2-4)	77	77
TM 57 (1-6)	79	79
TM 30 (2-4)	82	83
TM 30 (1-6)	86	86

* Results are statistically significant at the α =.05 level unless otherwise indicated with a letter.

** Test fields indicate the use of a boundary filter on the reference data for comparison with the classification data - a 2x2 filter on 57m data is compared with a 4x4 filter on 30m data.

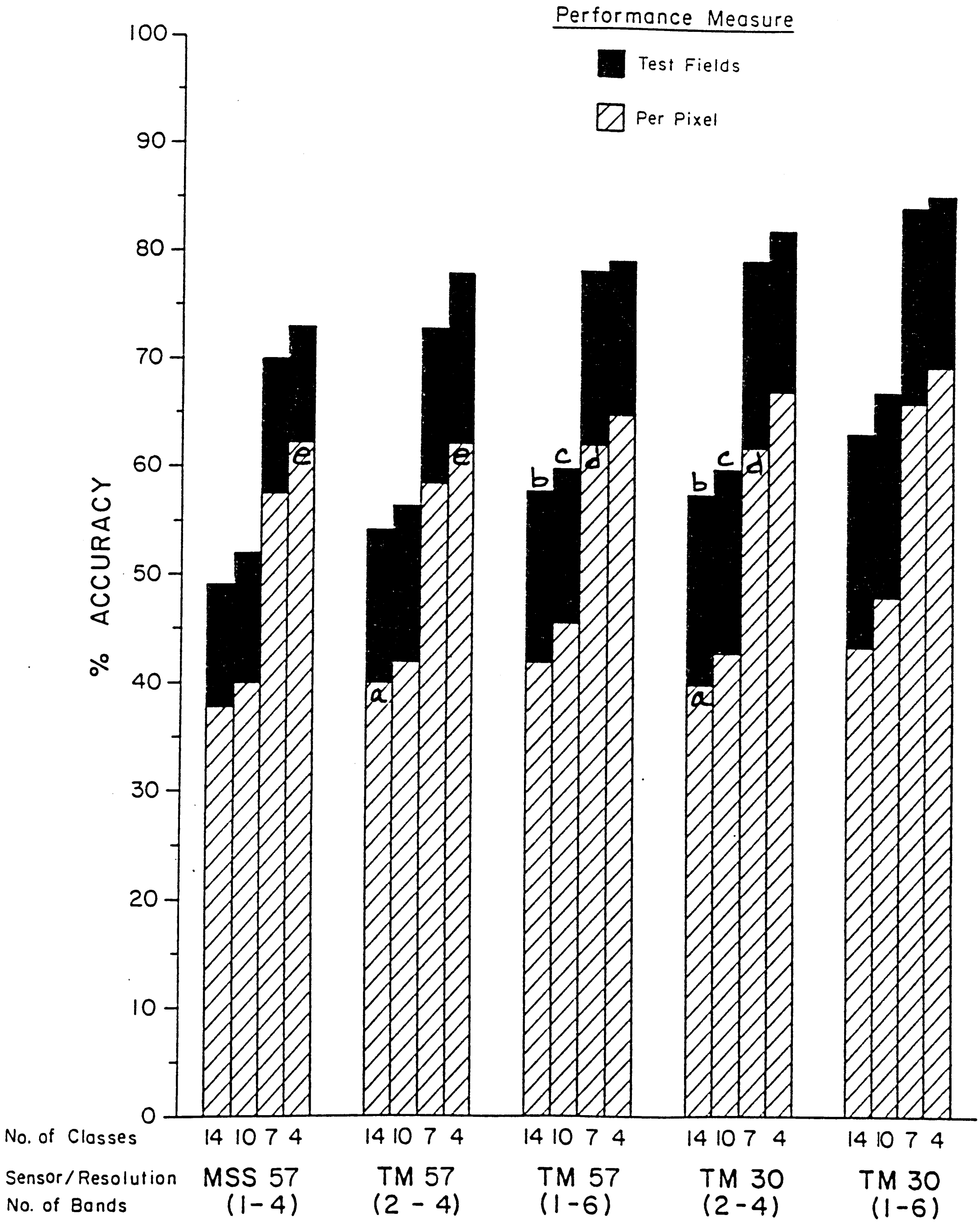

Figure 21. Overall classification accuracies of actual MSS data and various spatial/spectral combinations of TM data for May 1984. The results demonstrate differences in the number of resource classes and performance measure used. Results are statistically significant at the $\alpha = .05$ level unless otherwise indicated with a letter.

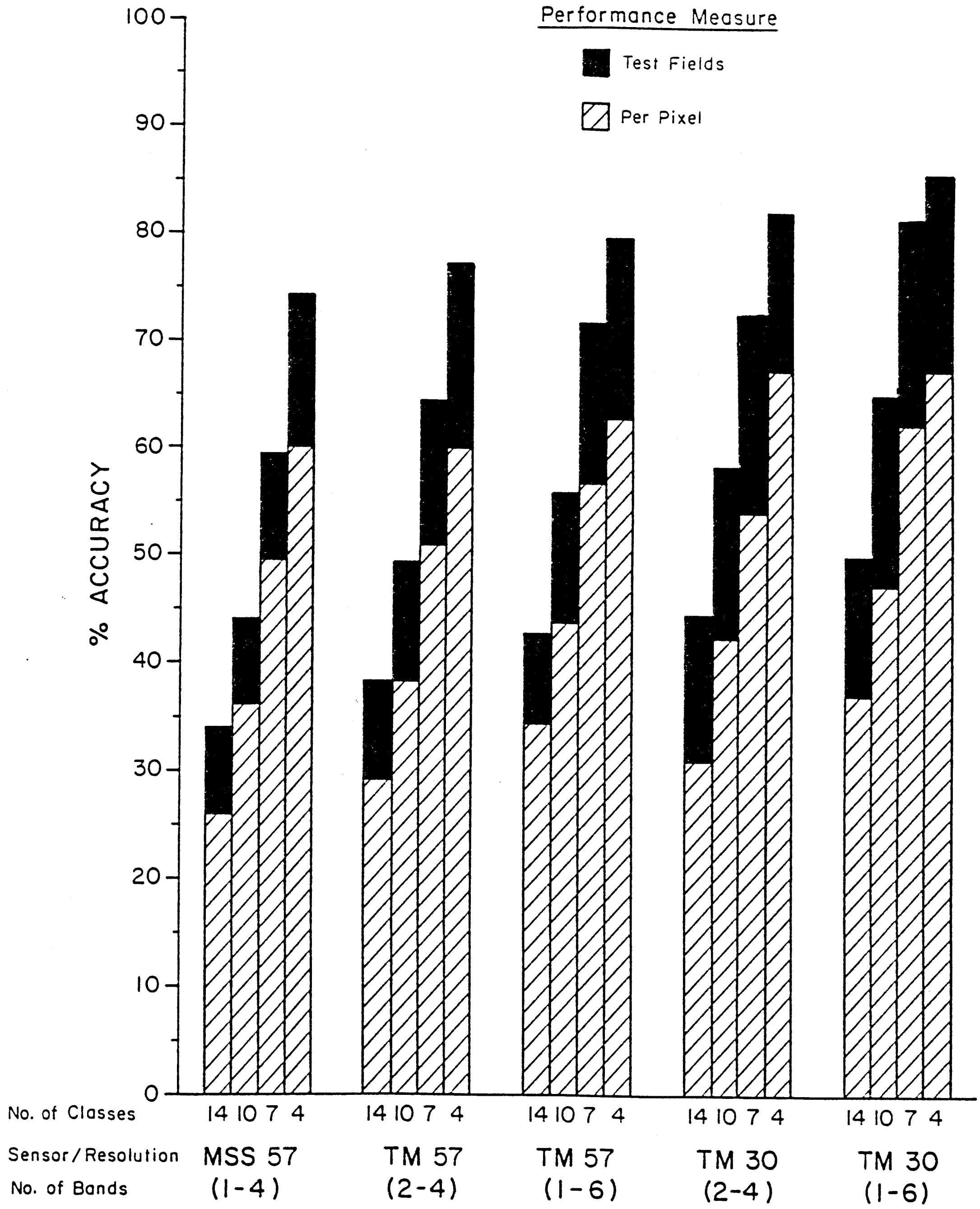

Figure 22. Normalized classification accuracies of actual MSS data and various spatial/spectral combinations of TM data for May 1984. The results demonstrate differences in the number of resource classes and performance measure used. The normalized data do not have a statistical significance test.

important than the spatial resolution for classifying cover types in Itasca State Park. The normalized results are consistently lower than the traditional overall accuracy results for all cases. The reason, the inclusion of errors of omission and commission, is obvious. Figure 23 indicates that this normalized value is more closely related to individual class accuracy value than to overall classification accuracy. The accuracy of an individual cover type (e.g., red pine or water) is individual class accuracy. As can be seen in this figure, the difference is more important when there are many classes (e.g., 7–14) than with a few aggregated classes (e.g., 4).

The results do not support the hypothesis that lower classification accuracies should accompany the finer spatial resolutions in a forest environment. In fact, the 30m TM with the full complement of reflective bands had higher classification accuracies than did the 57m TM using the same bands.

One variable that I did not hold constant was radiometric resolution. The TM sensor has a quantization of 256 levels (ability to detect 256 "gray" levels), while the MSS has a quantization level of 64. Therefore, some of the increased accuracy implied by increased spectral resolution in this Itasca Park study is in fact confounded with the increased radiometric resolution; however, spectral/radiometric confounding is constant for all real and degraded TM data. The results of Williams et al. (1984) may, however, clarify the likely effect of spectral and radiometric resolution. In their study of TM and MSS classifications of general land use categories near Washington,

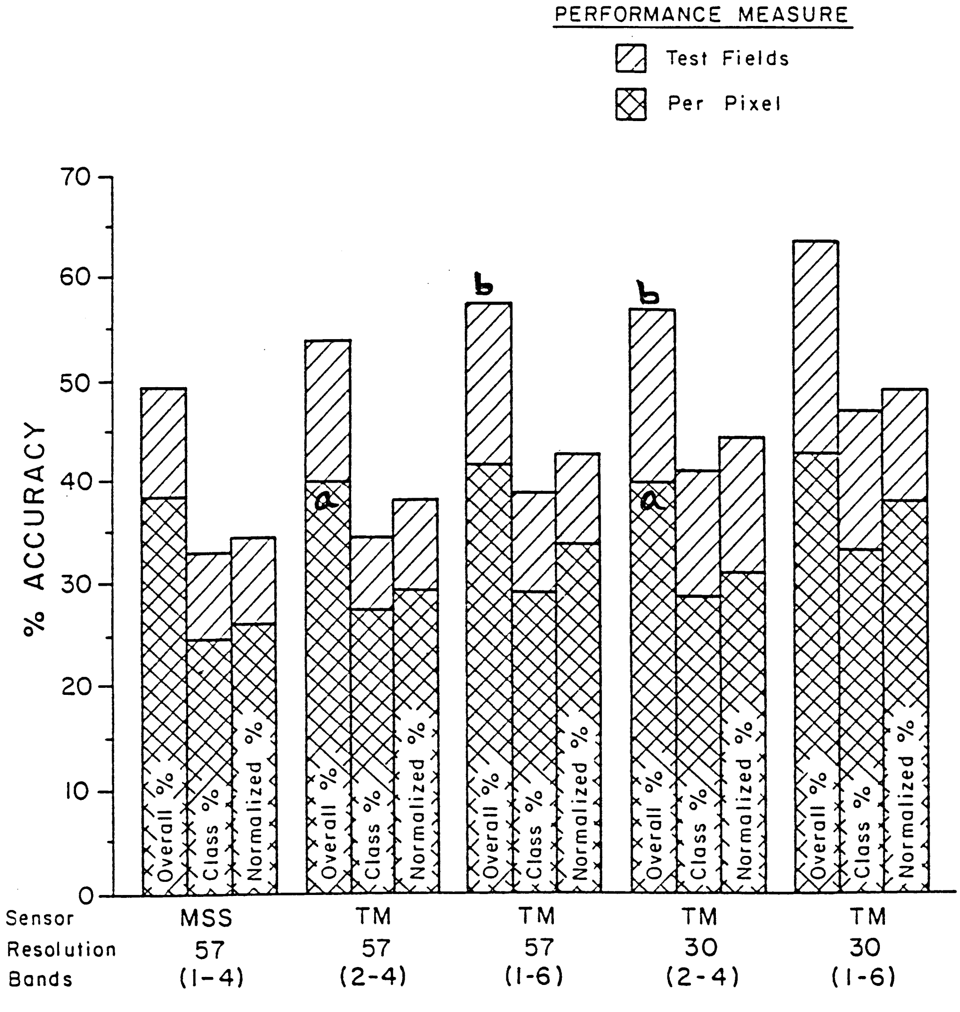

Figure 23. Comparison of overall, class, and normalized accuracies for 57m MSS, 57m TM, and 30m TM data using the per pixel and test field performance measures, and 14 resource classes. Results are statistically significant at the $\alpha = .05$ level unless otherwise indicated with a letter. Normalized data do not have a significance test.

D.C., they found that the greatest level of variance between TM and MSS data was accounted for by the spectral wave band variable, providing an average increase in classification accuracy of 6%. They claimed that this constituted a 21% relative improvement from TM data with respect to Landsat MSS data [i.e. percent relative improvement=(high accuracy value - low accuracy value)/(low accuracy value) X 100]. They determined that the second greatest variance was accounted for by the radiometric variable, providing a 5% increase in percent correctly classified pixels - a 19% relative improvement of TM over MSS data. Williams et al. found that spatial resolution accounted for only a 2% relative improvement of TM over MSS data.

Misregistration and boundary (mixed) pixels are two factors that may increase the probability of misclassification. When a series of boundary filters were used on 57m and 30m reference data, some interesting results emerged. Using a 2 x 2 pixel filter, 50% of the 57m reference data were found to be boundary pixels, while the same filter on 30m data yielded 31% boundary pixels. Successively larger boundary filters (3 x 3 and 4 x 4 pixels in size) were used on the 30m reference data to eliminate all but the centers of larger stands. The 3 x 3 filter contained 74% boundary pixels and the 4 x 4 filter contained 86% boundary pixels. Using this 4 x 4 filter on the reference data resembles the conventional test field approach for testing classification results in which only pure, homogeneous areas are used for comparing the reference data to the Landsat classification.

Figure 24 illustrates the effect the boundary pixels have on accuracy results. Logically, the more boundary pixels that are eliminated using successively larger filters, the higher the accuracies. The overall accuracies increased from 17-20% above the per pixel (wall to wall) comparison for TM 30m 1-6 data using this test field approach. This trend is consistent across all spectral/spatial combinations (Figures 19 and 20). As will be seen in the next section, this trend continues to hold true for all band/date combinations as well.

A selected set of individual class accuracy results is shown in Table 11 and Figures 25 and 26. Figure 25 illustrates individual differences for aspen/birch, red pine, upland hardwood, and upland conifer classes between MSS data and TM 30m (with all six reflective bands). It further supports the idea that the TM data provides higher accuracies for individual classes. With ten resource classes, for example, and concentrating on the red pine cover type, the TM data has a 14% increase in classification accuracy over MSS data using the per pixel approach. Figure 26 illustrates overall classification accuracy differences between seven aggregated classes for TM 30m data using all six reflective bands. The data compare the conventional percent-correctly-classified results with the normalized-accuracy results using the per pixel and test field performance measures. Generally speaking, the classification accuracies are higher for the upland hardwood, water, field/grass, and cutover cover types. Accuracies for the upland

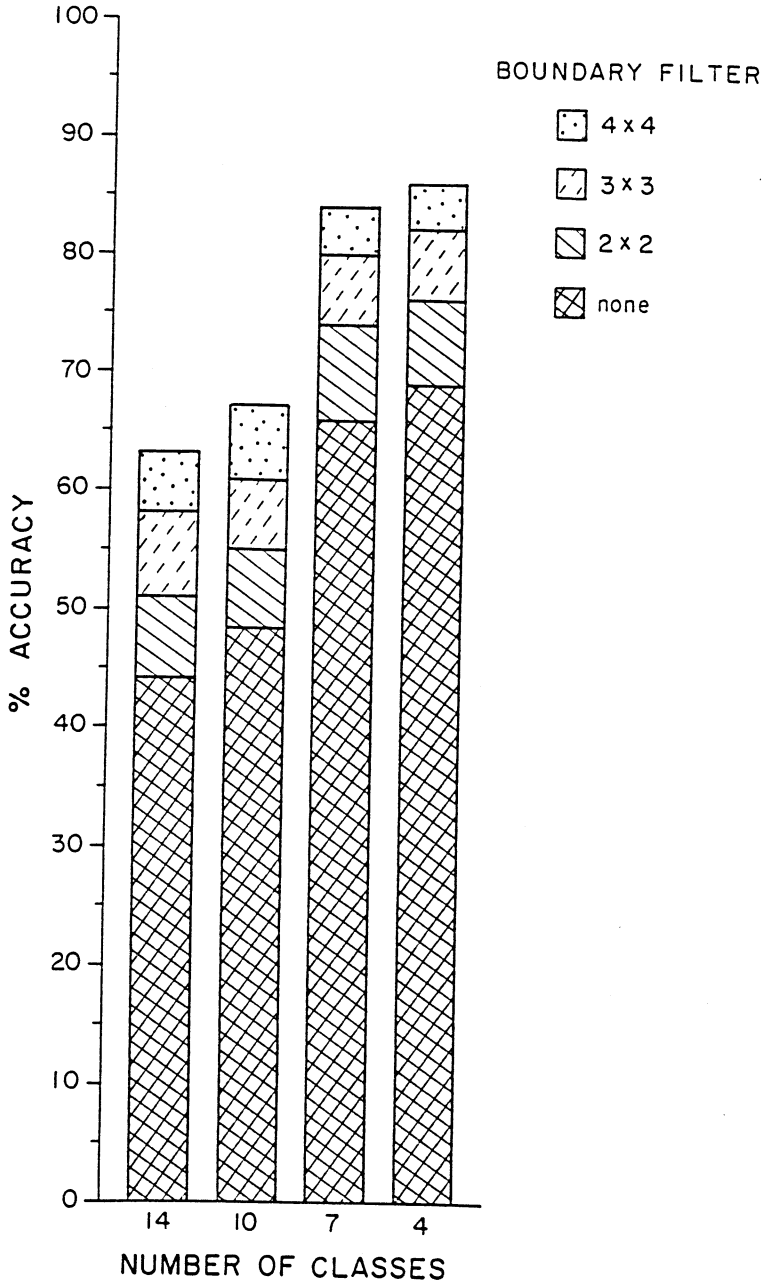

Figure 24. Effect of successively larger boundary filters and number of cover type classes on overall classification accuracies of 30m TM data using all six reflective bands. Results are statistically significant at the $\alpha = .05$ level unless otherwise indicated with a letter.

Table 11. Individual class accuracies for seven cover types using the per pixel (no filter) and test field (4x4 filter) approach. The top number associated with each band/date combination is the conventional percent correct, while the bottom number is the normalized data that includes errors of omission and commission.

Sensor/ Spatial/ Spectral Band Combination	Cover Type: Upld Hwd	Upld Cnfr	Water	Fld/ Grass	Mrsh/ L.Shrb	Lwld Cnfr	Cutover
Per Pixel							
MSS 57 (1-4)	70	43	73	51	18	14	47
	40	34	74	65	31	42	54
TM 57 (2-4)	72	41	72	59	14	20	52
	42	36	72	69	35	44	56
TM 57 (1-6)	75	47	69	59	22	20	58
	47	41	77	67	38	57	75
TM 30 (2-4)	75	46	68	61	19	27	50
	46	43	83	67	39	46	55
TM 30 (1-6)	77	51	72	69	26	33	71
	54	47	79	71	47	60	77
Test Fields							
MSS 57 (1-4)	75	54	92	73	31	17	51
	50	43	88	78	47	49	58
TM 57 (2-4)	79	53	95	84	30	23	60
	57	47	91	81	57	51	63
TM 57 (1-6)	83	59	94	83	45	30	66
	63	57	91	81	62	68	82
TM 30 (2-4)	82	62	98	96	56	38	54
	62	63	96	93	70	61	68
TM 30 (1-6)	86	68	98	99	61	50	79
	75	68	95	94	80	75	88

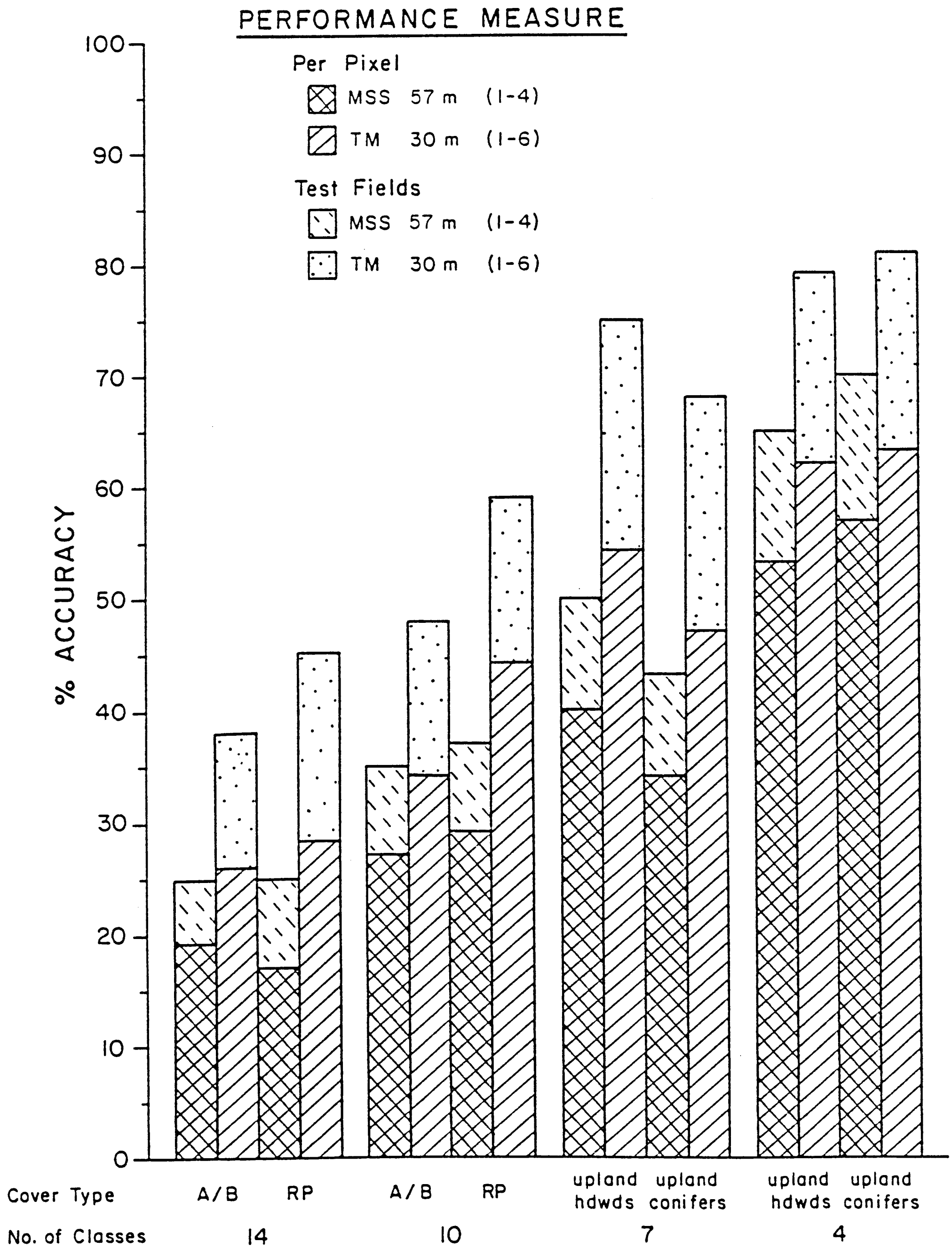

Figure 25. Comparison of 57m MSS and 30m TM data for identification of individual cover types, aspen/birch and red pine, and aggregated classes of upland hardwood and upland conifer.

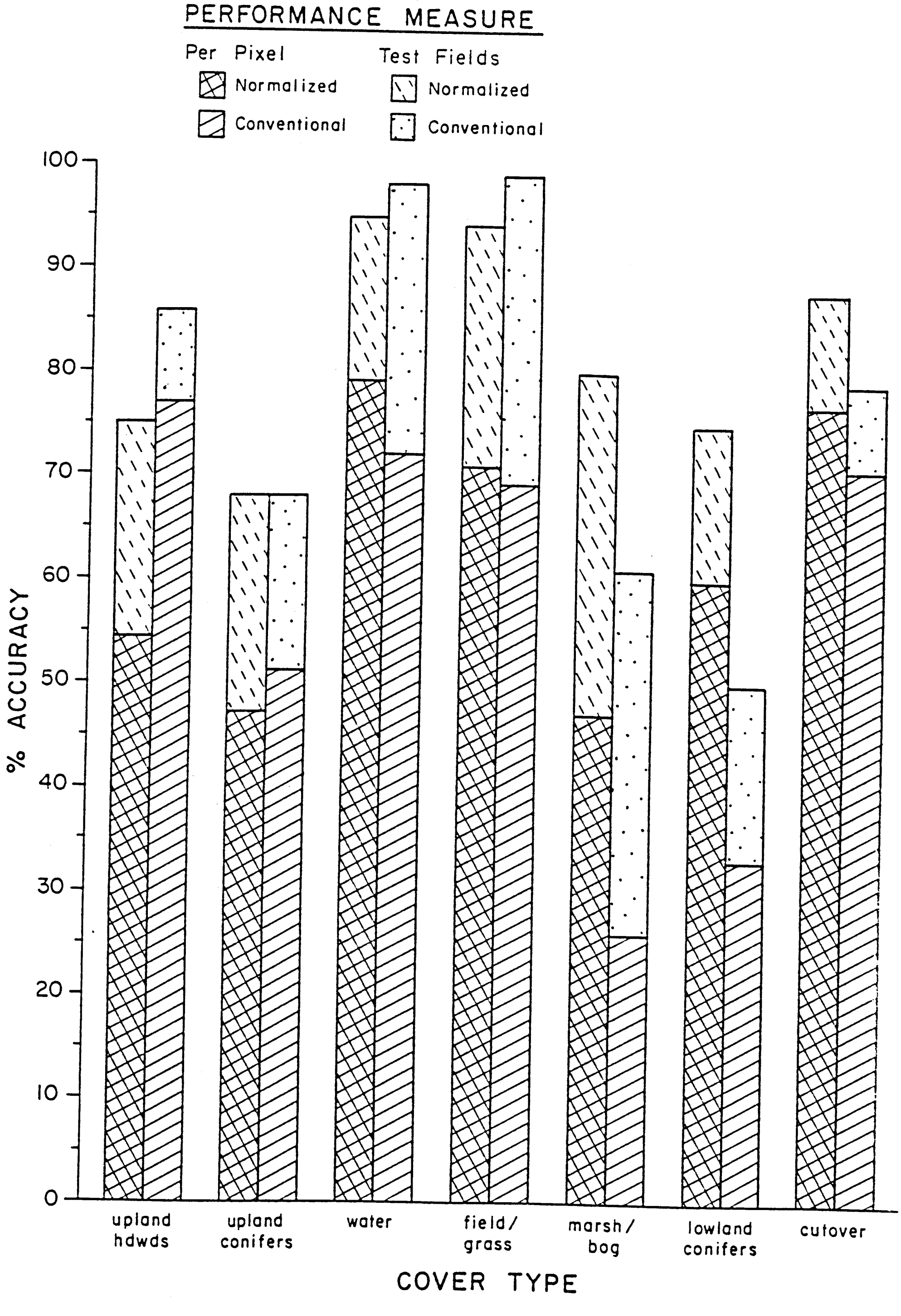

Figure 26. Individual class accuracies for seven classes using 30m TM data with all six reflective bands.

conifer, marsh/bog, and lowland conifer cover types are lower and more variable depending on the performance measure used.

Using Landsat MSS data, Mead and Meyer (1977) mapped eleven categories of land cover in northern Minnesota that were relatively broad types (e.g., upland hardwoods, lowland conifer, brush/shrub, sedge meadows, water, etc.) using MSS data. Using the supervised classification procedure, they obtained accuracies of 43-53% using a method that they called an "evaluation area." This evaluation area is similar to the method used in this study referred to as wall to wall or pixel by pixel evaluation of accuracy performance. Using similar cover types (7 classes in this study) and a similar evalution method, I obtained overall accuracies of 63-67% with TM data. Relatively speaking, this is a 10-20% increase in overall classification performance. Although significant, this increase does not convince me that Landsat TM data is sufficient for detailed site-specific forest management. However, satellite data classification of Level II (and some Level III) classes is approaching reasonable accuracies for county and statewide inventories, and certain ecological studies interested in determining biophysical relationships such as LAI and productivity.

Analysis of contingency tables (error matrices) provide further insight into individual classification errors (Tables 12-17). Tables 12-15 are error matrices for 57m MSS and 30m TM data (May 18, 1984) using per pixel and test field performance measures, respectively, for 14 classes. Tables 16 and 17 are error matrices for TM data using seven aggregated classes. Errors of omission and commission will be examined in greater detail for red pine, marsh/bog, and cutover cover types only.

Examination of the red pine cover type (and upland conifer) demonstrates that many pixels that are actually red pine were classified as aspen/birch (or upland hardwoods for seven classes). The primary reason for this misclassification is canopy closure. In many areas of the Park, the mature red pine is dying and breaking up, and the aspen/birch understory is achieving codominance in the stand.

The marsh/bog cover type has more pixels misclassified as aspen/birch, water, and lowland shrub than those pixels correctly classified as marsh/bog. This cover type is extremely variable, and it occupies many small areas that are scattered throughout the Park. It is often associated with the water and lowland shrub cover types. The misclassifications may in fact be true mixtures or gradients of these three cover types.

The majority of pixels for the cutover cover type are correctly classified (41% for 57m MSS data and 71% for 30m TM data). Misclassifications are primarily attributed to the aspen/birch (upland hardwoods for the seven classes case) and lowland shrub cover types. This is not a surprising result since many of the older cutover areas have many young aspen sprouts and saplings, as well as herbaceous materials and shrubs. The shrubby vegetation and dead grasses of the lowland shrub cover type closely resemble the vegetation of cutover areas in the early spring.

Table 12. Error matrix for 57 m MSS data using the per pixel performance measure and 14 classes.

	Total	#Errs	%Comm	A/B	RP	W	JP	F/G	M/B	WP	NH	LS	S-F	TK	BS	CO	A/NH
				Reference Data Class:													
A/B	13234	6207	46.3	7027	1394	300	258	25	520	319	920	397	172	116	42	108	1636
RP	3708	2273	61.3	724	1435	197	235	8	124	164	196	125	137	80	104	11	168
W	3806	1399	35.8	317	137	2407	31	5	270	21	148	162	41	13	6	31	217
JP	937	805	85.9	149	246	18	132	0	18	20	67	57	89	38	48	2	53
F/G	1625	1504	92.6	611	282	44	58	121	57	70	102	61	27	11	9	15	147
M/B	505	364	72.1	44	23	42	3	6	141	7	26	98	32	11	13	47	12
WP	553	517	93.5	200	254	4	6	0	9	36	16	1	2	0	4	1	20
NH	3217	2756	85.7	1484	98	53	35	16	112	59	461	84	27	19	2	111	656
LS	1611	1468	91.1	338	108	53	61	1	208	25	190	143	67	19	15	187	196
S-F	1310	1138	86.9	302	116	78	60	3	49	19	186	123	172	69	45	7	81
TK	936	897	95.8	299	178	21	66	0	24	41	74	51	29	39	17	2	75
BS	387	361	93.3	76	107	11	21	0	9	13	14	31	34	28	26	3	14
CO	2069	1558	75.3	593	79	22	35	40	187	33	210	94	3	12	5	511	245
A/NH	1689	1309	77.5	776	62	65	19	11	73	24	167	47	7	4	3	51	380
			TOTAL:	12940	4519	3315	1050	236	1801	851	2777	1474	839	459	339	1087	3900
			#CORR:	7027	1435	2407	132	121	141	36	461	143	172	39	26	511	380
			%CORR:	54.3	31.3	72.6	12.6	51.3	7.8	4.2	16.6	9.7	20.5	8.5	7.7	47.0	9.7
			#ERRS:	5913	3084	908	918	115	1660	815	2316	1331	667	420	313	576	3520
			%OM :	45.7	68.2	27.4	87.4	48.7	92.2	95.8	83.4	90.3	79.5	91.5	92.3	53.0	90.3

class zero pix = 29949; non-zero pix = 35587; correct pix = 13031; overall acc. = 36.6; avg. class acc. = 25.3

KEY: A/B = aspen/birch, RP = red pine, W = water, JP = jack pine, F/G = field/grass, M/B = marsh/bog, WP = white pine, NH = northern hardwoods, LS = lowland shrubs, S-F = white spruce-balsam fir, TK = tamarack, BS = black spruce, CO = cutover (and various stages regeneration), A/NH = aspen/northern hardwoods mix.

Table 13. Error matrix for 57 m MSS data using the test field performance measure and 14 classes.

				Reference Data Class:													
	Total	#Errs	%Comm	A/B	RP	W	JP	F/G	M/B	WP	NH	LS	S-F	TK	BS	CO	A/NH
A/B	7109	2202	31.0	4907	491	27	119	8	40	107	422	43	62	31	8	51	793
RP	1704	767	45.0	304	937	58	99	0	12	60	62	10	62	21	24	6	49
W	1944	306	15.5	98	28	1671	10	1	36	1	33	17	11	2	0	9	60
JP	403	334	82.9	71	132	8	69	0	2	6	20	6	42	10	10	1	26
F/G	829	731	88.2	371	134	7	36	98	3	26	50	3	12	0	0	7	82
M/B	166	107	64.5	8	4	10	2	2	59	0	13	25	7	1	1	32	2
WP	319	299	93.7	114	160	0	3	0	1	20	6	0	1	0	4	1	9
NH	1719	1466	85.3	929	21	6	13	4	23	13	253	8	9	3	0	83	354
LS	641	610	95.2	166	18	7	32	0	31	8	101	31	17	1	2	132	95
S-F	518	439	84.7	172	42	16	34	1	6	3	79	24	79	21	8	1	32
TK	415	404	97.3	158	85	6	32	0	1	18	31	9	13	11	2	1	48
BS	157	149	94.9	44	61	2	6	0	1	3	3	4	11	9	8	0	5
CO	1055	681	64.5	333	19	1	8	13	43	12	115	15	0	2	0	374	120
A/NH	910	675	74.2	491	17	6	7	7	10	5	93	5	3	1	0	30	235
			TOTAL:	8166	2149	1825	470	134	268	282	1281	200	329	113	67	728	1910
			#CORR:	4907	937	1671	69	98	59	20	253	31	79	11	8	374	235
			%CORR:	60.1	43.6	91.6	14.7	73.1	22.0	7.1	19.8	15.5	24.0	9.7	11.9	51.4	12.3
			#ERRS:	3259	1212	154	401	36	209	262	1028	169	250	102	59	354	1675
			%OM :	39.9	56.4	8.4	85.3	26.9	78.0	92.9	80.2	84.5	76.0	90.3	88.1	48.6	87.7

class zero pix = -32768; non-zero pix = 17922; correct pix = 8752; overall acc. = 48.8; avg. class acc. = 32.6

KEY: A/B = aspen/birch, RP = red pine, W = water, JP = jack pine, F/G = field/grass, M/B = marsh/bog, WP = white pine, NH = northern hardwoods, LS = lowland shrubs, S-F = white spruce-balsam fir, TK = tamarack, BS = black spruce, CO = cutover (and various stages regeneration), A/NH = aspen/northern hardwoods mix.

Table 14. Error matrix for 30 m TM data using the per pixel performance measure and 14 classes.

	Total	#Errs	%Comm	Reference Data Class: A/B	RP	W	JP	F/G	M/B	WP	NH	LS	S-F	TK	BS	CO	A/NH
A/B	59864	25816	43.1	34048	5287	1412	940	42	1819	1324	4189	1446	795	391	183	433	7555
RP	10988	5282	48.1	2029	5706	176	466	20	168	579	399	290	510	89	180	35	341
W	12214	3086	25.3	533	250	9128	50	4	998	37	222	512	76	42	7	53	302
JP	7769	6455	83.1	1695	2189	185	1314	10	201	294	447	317	340	100	198	29	450
F/G	5939	5419	91.2	1469	1093	235	279	520	484	276	416	341	135	23	56	90	522
MB	2049	1214	59.2	175	68	138	52	23	835	20	97	375	75	9	33	99	53
WP	2313	2060	89.1	480	1125	31	64	2	29	253	97	45	63	14	42	10	58
NH	7478	5562	74.4	2495	257	232	22	10	220	200	1916	159	41	31	4	95	1796
LS	4562	3683	80.7	747	241	265	100	9	1155	28	246	879	122	152	42	179	397
S-F	6768	6042	89.3	1763	552	366	258	10	274	98	899	587	726	273	123	40	799
TK	3289	2820	85.7	659	548	71	205	15	37	105	244	307	248	469	270	10	101
BS	1030	906	88.0	90	249	30	90	0	12	19	44	94	122	127	124	1	28
CO	6184	3107	50.2	1128	123	194	127	59	379	44	253	212	18	31	4	3077	535
A/NH	10037	7340	73.1	4651	180	304	21	28	251	111	1345	228	32	21	3	165	2697
			TOTAL:	51962	17868	12767	3988	752	6862	3388	10814	5792	3303	1772	1269	4313	15634
			#CORR:	34048	5706	9128	1314	520	835	253	1916	879	726	469	124	3077	2697
			%CORR:	65.5	31.9	71.5	32.9	69.1	12.2	7.5	17.7	15.2	22.0	26.5	9.8	71.3	17.3
			#ERRS:	17914	12162	3639	2674	232	6027	3135	8898	4913	2577	1303	1145	1236	12937
			%OM :	34.5	68.1	28.5	67.1	30.9	87.8	92.5	82.3	84.8	78.0	73.5	90.2	28.7	82.7

class zero pix = -32768; non-zero pix = 140484; correct pix = 61692; overall acc. = 43.9; avg. class acc. = 33.6

KEY: A/B = aspen/birch, RP = red pine, W = water, JP = jack pine, F/G = field/grass, M/B = marsh/bog, WP = white pine, NH = northern hardwoods, LS = lowland shrubs, S-F = white spruce-balsam fir, TK = tamarack, BS = black spruce, CO = cutover (and various stages regeneration), A/NH = aspen/northern hardwoods mix.

Table 15. Error matrix for 30 m TM data using the test field performance measure and 14 classes.

	Total	#Errs	%Comm	A/B	RP	W	JP	F/G	M/B	WP	NH	LS	S-F	TK	BS	CO	A/NH
				Reference Data Class:													
A/B	23829	5297	22.2	18532	1048	26	127	0	9	168	1215	16	186	22	3	192	2285
RP	3756	1105	29.4	579	2651	6	123	0	0	116	44	2	122	6	5	18	84
W	6045	165	2.7	45	8	5880	4	0	44	0	8	21	5	0	0	8	22
JP	2286	1774	77.6	542	776	9	512	0	2	74	74	7	84	1	7	9	189
F/G	1345	1019	75.6	378	236	8	116	326	3	38	54	3	16	1	13	35	118
M/B	175	76	43.4	13	0	3	9	2	99	0	0	9	1	0	0	39	0
WP	733	648	88.4	132	420	0	29	0	0	85	20	2	16	0	20	4	5
NH	2529	1864	73.7	1057	29	4	3	2	0	26	665	0	9	6	0	54	674
LS	495	441	89.1	158	11	4	14	0	62	3	22	54	18	16	1	58	74
S-F	1477	1255	85.0	635	90	22	76	0	5	7	170	7	222	11	2	5	225
TK	610	560	91.8	182	151	4	67	0	0	7	43	5	47	50	47	0	7
BS	208	200	96.2	27	81	1	30	0	0	7	5	2	23	12	8	1	11
CO	2520	600	23.8	295	15	3	17	0	9	0	79	2	1	2	0	1920	177
A/NH	3834	2907	75.8	2364	12	3	2	0	3	15	413	1	0	3	0	91	927
			TOTAL:	24939	5528	5973	1129	330	236	546	2812	131	750	130	106	2434	4798
			#CORR:	18532	2651	5880	512	326	99	85	665	54	222	50	8	1920	927
			%CORR:	74.3	48.0	98.4	45.3	98.8	41.9	15.6	23.6	41.2	29.6	38.5	7.5	78.9	19.3
			#ERRS:	6407	2877	93	617	4	137	461	2147	77	528	80	98	514	3871
			%OM :	25.7	52.0	1.6	54.7	1.2	58.1	84.4	76.4	58.8	70.4	61.5	92.5	21.1	80.7

class zero pix = -32768; non-zero pix = 49842; correct pix = 31931; overall acc. = 64.1; avg. class acc. = 47.2

KEY: A/B = aspen/birch, RP = red pine, W = water, JP = jack pine, F/G = field/grass, M/B = marsh/bog, WP = white pine, NH = northern hardwoods, LS = lowland shrubs, S-F = white spruce-balsam fir, TK = tamarack, BS = black spruce, CO = cutover (and various stages regeneration), A/NH = aspen/northern hardwoods mix.

Table 16. Error matrix for 30 m TM data using the per pixel performance measure and 7 aggregated classes.

				Reference Data Class:						
	Total	#Errs	%Comm	UH	UC	W	F/G	M/B and LS	LC	CO
UH	77379	16687	21.6	60692	9210	1948	80	4123	633	693
UC	27838	13301	47.8	9457	14537	758	42	1911	1019	114
W	12214	3086	25.3	1057	413	9128	4	1510	49	53
F/G	5939	5419	91.2	2407	1783	235	520	825	79	90
M/B & LS	6611	3367	50.9	1715	706	403	32	3244	236	275
LC	4319	3329	77.1	1166	1586	101	15	450	990	11
CO	6184	3107	50.2	1916	312	194	59	591	35	3077
			TOTAL:	78410	28547	12767	752	12654	3041	4313
			#CORR:	60692	14537	9128	520	3244	990	3077
			%CORR:	77.4	50.9	71.5	69.1	25.6	32.6	71.3
			#ERRS:	17718	14010	3639	232	9410	2051	1236
			%OM :	22.6	49.1	28.5	30.9	74.4	67.4	28.7

class zero pix = -32768; non-zero pix = 140484; correct pix = 82188; overall acc. = 65.6; avg. class acc. = 56.9

KEY: UH = upland hardwoods, UC = upland conifers, W = water, F/G = field/grass, M/B & LS = marsh/bog and lowland shrubs, LC = lowland conifers, CO = cutover (and various stages of regeneration)

Table 17. Error matrix for 30 m TM data using the test field performance measure and 7 aggregated classes.

	Total	#Errs	%Comm	UH	UC	W	F/G	M/B and LS	LC	CO
				Reference Data Class:						
UH	30192	2060	6.8	28132	1625	33	2	29	34	337
UC	8252	2849	34.5	2699	5403	37	0	25	52	36
W	6045	165	2.7	75	17	5880	0	65	0	8
F/G	1345	1019	75.8	550	406	8	326	6	14	35
M/B & LS	670	446	66.6	267	56	7	2	224	17	97
LC	818	701	85.7	275	413	5	0	7	117	1
CO	2520	600	23.8	551	33	3	0	11	2	1920
			TOTAL:	32549	7953	5973	330	367	236	2434
			#CORR:	28132	5403	5880	326	224	117	1920
			%CORR:	86.4	67.9	98.4	98.8	61.0	49.6	78.9
			#ERRS:	4417	2550	93	4	143	119	514
			%OM :	13.6	32.1	1.6	1.2	39.0	50.4	21.1

class zero pix = -32768; non-zero pix = 49842; correct pix = 42002; overall acc. = 84.3; avg. class acc. = 77.3

KEY: UH = upland hardwoods, UC = upland conifers, W = water, F/G = field/grass, M/B & LS = marsh/bog and lowland shrubs, LC = lowland conifers, CO = cutover (and various stages of regeneration)

The test field performance (Tables 13, 15, and 17) for the MSS and TM data demonstrates many of the same trends, however, there are fewer misclassifications. As mentioned previously, this is due to the pure, homogeneous nature of this performance measure.

Another interesting way to present these data is by comparing the proportions (%) of the vegetation cover types on the reference map to the cover type proportions on the MSS and TM classification maps. This comparison is presented in Table 18. Percentages of cover types resulting from the Landsat classifications are relatively similar to those of the reference map . Apparently, some of the errors of omission and commission are cancelling each other. There are some consistent differences, however, and I cannot be sure of the cause. For inventories that simply require percentages of general forest cover types, and do not require locational statistics, this may be a very useful, and efficient way to obtain that information.

4.3. Spectral Band/Date Combination Study

The primary objective of this study was to determine which set of Thematic Mapper spectral bands, and which date or set of dates would yield the highest classification accuracies for cover type discrimination in Itasca State Park. The band/date combinations used in this study are listed in Table 6. All data are from the Landsat-5 Thematic Mapper sensor.

Table 18. Comparison of reference map, MSS (57m), and TM (30m) classification map proportions (%) of vegetation cover types in Itasca State Park and surrounding borders.

	Total Proportions (%)				
		MSS (57m)		TM (30m)	
Cover Types	Reference Map	Per Pixel	Test Fields	Per Pixel	Test Fields
Aspen/Birch	35	37	40	43	47
Aspen/No. Hdwd Mix	11	5	5	7	8
Red Pine	12	10	10	8	8
Jack Pine	3	3	2	6	5
E. White Pine	2	2	2	2	2
Spruce-Fir	2	4	3	5	3
No. Hardwoods	8	9	10	5	5
Tamarack	1	3	2	2	1
Black Spruce	0.9	1	1	0.7	0.4
Lowland Shrubs	4	5	4	3	1
Marsh and Bog	5	1	1	2	0.4
Field and/or Grass	0.8	5	5	4	3
Cutover	3	6	6	4	5
Water	12	10	10	9	12
Total (acres)	36,060				
(pixels)		35,587	17,922	140,484	49,842

4.3.1. Spectral Response Analysis

Mean spectral response from selected aggregated training samples are shown in Table 19 and plotted in Figures 27-32. Because of the difficulty of illustrating all of the various cover type/band/date combinations on one graph, only a few cover types were selected to demonstrate the general trends.

All six graphs illustrate the temporal (February, May, July, September) spectral response patterns of six cover types (aspen/birch, red pine, cutover, water, tamarack, and black spruce) over the six reflective bands of TM data. Figure 27 shows the response patterns for the aspen/birch cover type. The February date clearly illustrates the influence of a snow background on spectral response. Snow has a high reflectance in the visible bands, a lower reflectance in the near infrared (NIR), and a much lower response in the middle infrared (MIR) bands (due to the high moisture content). The aspen/birch cover type reflects higher in the red band (band 3) and lower in the NIR (band 4) in the winter because there is little chlorophyll (perhaps some in the bark) to absorb the red and NIR. With the increase in leaf area during the spring-summer, there is a corresponding low reflectance in the red band and high reflectance in the NIR. The fall date also responds as expected, as the chlorophyll concentration and green leaf area decreases the response in the green band (band 2), and the NIR band

Table 19. Mean spectral response of aggregated training sets for selected resource classes from TM data - February, May, July, September, 1985.

Cover Type and Date	Landsat Band 1	2	3	4	5	7
	---- digital counts ----					
February						
Aspen/Birch	122	47	59	52	33	17
No. Hardwoods	125	48	59	53	32	16
Red Pine	71	23	23	40	14	5
Jack Pine	82	28	30	41	19	8
Spruce/Fir	99	35	40	42	25	11
Black Spruce	79	26	28	36	20	9
Tamarack	97	35	41	43	29	14
Cutover	200	90	110	89	35	17
Field/Grass	254	141	188	141	34	17
Water	255	137	183	136	31	15
May						
Aspen/Birch	75	30	24	112	75	22
No. Hardwoods	76	33	27	107	84	26
Red Pine	75	28	24	78	66	17
Jack Pine	76	29	27	75	66	23
Spruce/Fir	77	30	26	80	73	25
Black Spruce	77	29	26	72	56	19
Tamarack	78	32	27	81	60	20
Cutover	84	36	35	100	110	42
Field/Grass	106	48	62	92	155	64
Water	69	21	16	10	5	2
July						
Aspen/Birch	77	28	23	118	74	20
No. Hardwoods	77	30	24	120	79	22
Red Pine	77	28	24	82	51	15
Jack Pine	77	28	24	84	62	19
Spruce/Fir	76	29	23	100	69	20
Black Spruce	79	30	25	84	55	17
Tamarack	79	31	26	100	69	20
Cutover	81	33	29	123	101	31
Field/Grass	90	38	43	91	122	45
Water	74	23	18	13	5	2

Table 19 (cont.).

Cover Type and Date	Landsat Band 1	2	3	4	5	7
	—— digital counts ——					
<u>September</u>						
Aspen/Birch	60	23	24	57	59	20
No. Hardwoods	61	24	26	53	64	23
Red Pine	57	19	18	47	30	10
Jack Pine	57	20	18	41	38	13
Spruce/Fir	59	22	21	45	49	18
Black Spruce	58	21	18	43	33	11
Tamarack	59	23	21	52	41	11
Cutover	63	23	26	48	82	33
Field/Grass	65	27	27	75	90	30
Water	54	16	13	7	4	2

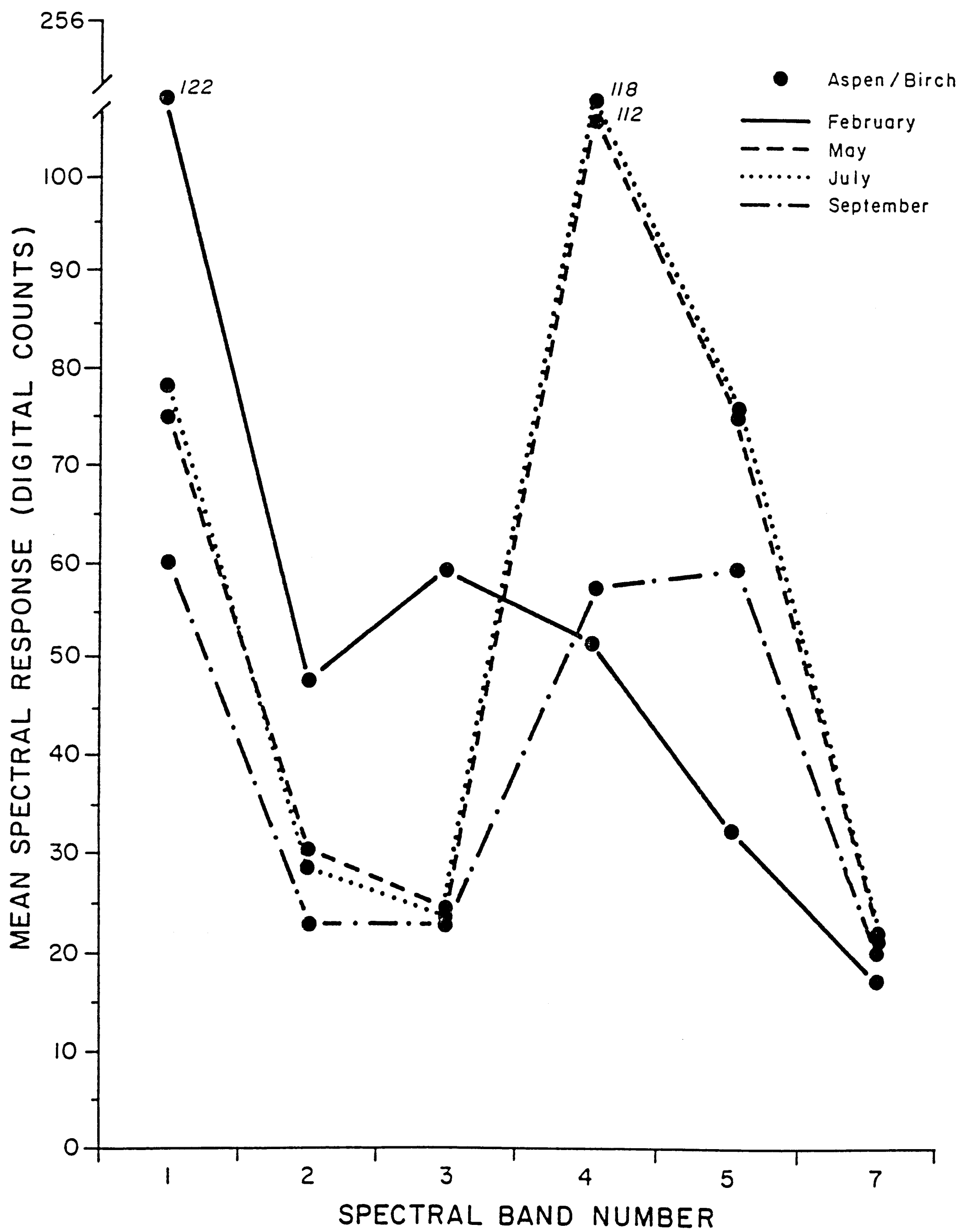

Figure 27. Spectral response patterns of aspen/birch over the six reflective bands of TM data for February 14, May 21, July 8, and September 26, 1985.

(band 4) decrease. There is also a large decrease in the response of the first MIR band (band 5). This may be caused by increased moisture in the soil, or it could be due to shadowing from the lower sun angle.

Figure 28 shows the response patterns for the red pine cover type. This cover type has the same basic responses, yet there are also some differences worth mentioning. The overall reflectance for the February date is not very different from the other dates in the visible bands, primarily because conifers maintain their leaf area (needles) all year round. In the winter, both the NIR and MIR response are low due to dormancy, shadows and/or moisture. The same pattern holds true for the September date. Again, May and July responses are not significantly different, except in the first MIR band (band 5).

Figure 29 overlays both the aspen/birch and red pine spectral responses. This demonstrates why the upland hardwoods and upland conifers are so separable with the TM data.

The cutover cover type follows patterns that are similar to the aspen/birch, yet the higher response in the NIR (band 4) is in July instead of May (Figure 30). This response would be expected due to the later leaf out of the shrubs, and green up of the grasses in a clearcut.

The water (snow and ice in February) responded exactly as expected (Figure 31). Water bodies absorb nearly all incident energy in both the near and middle infrared wavelengths, so there is very little energy available to be reflected at these wavelengths. The

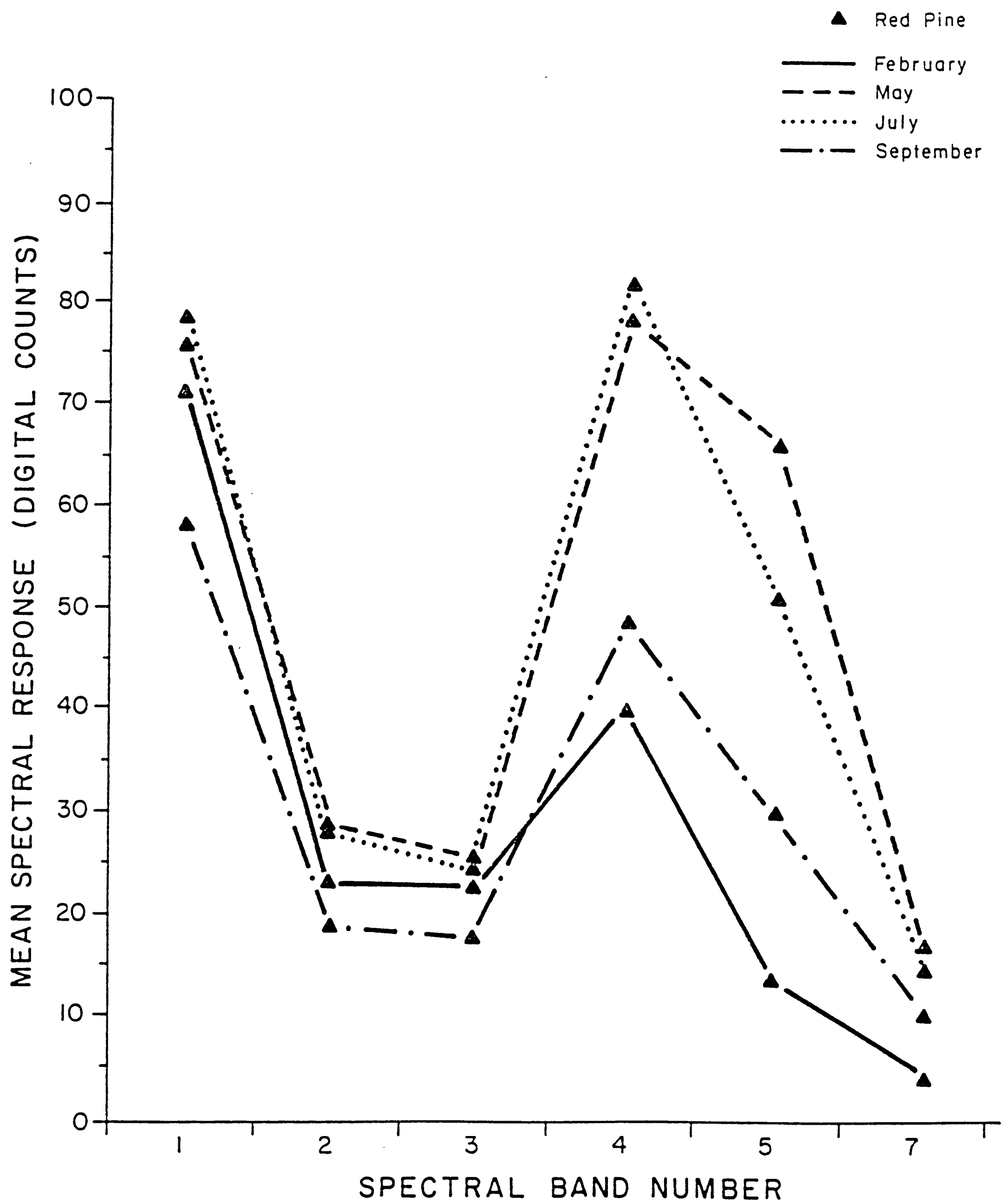

Figure 28. Spectral response patterns of red pine over the six reflective bands of TM data for February 14, May 21, July 8, and September 26, 1985.

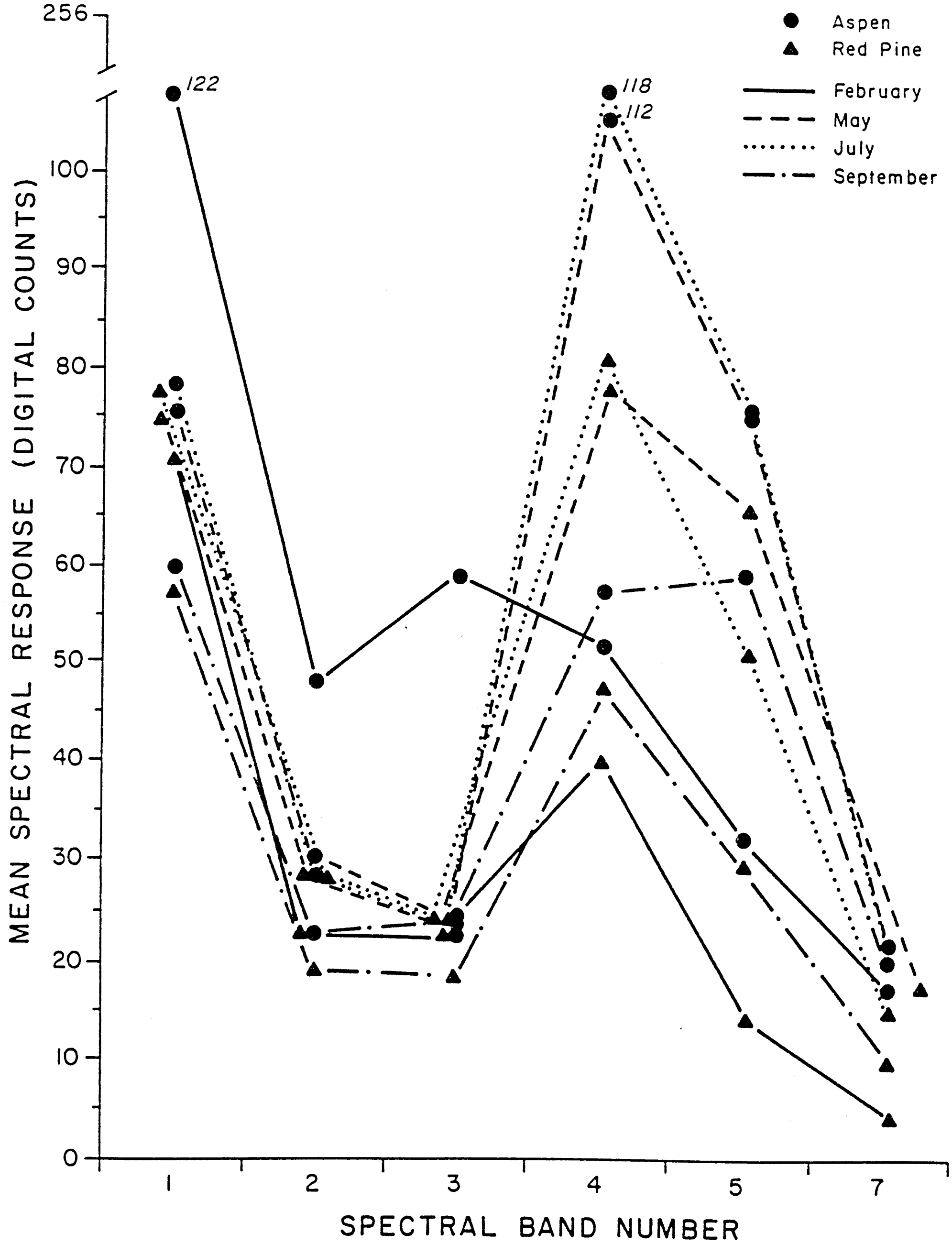

Figure 29. Spectral response patterns of aspen/birch and red pine over the six reflective bands of TM data for February 14, May 21, July 8, and September 26, 1985.

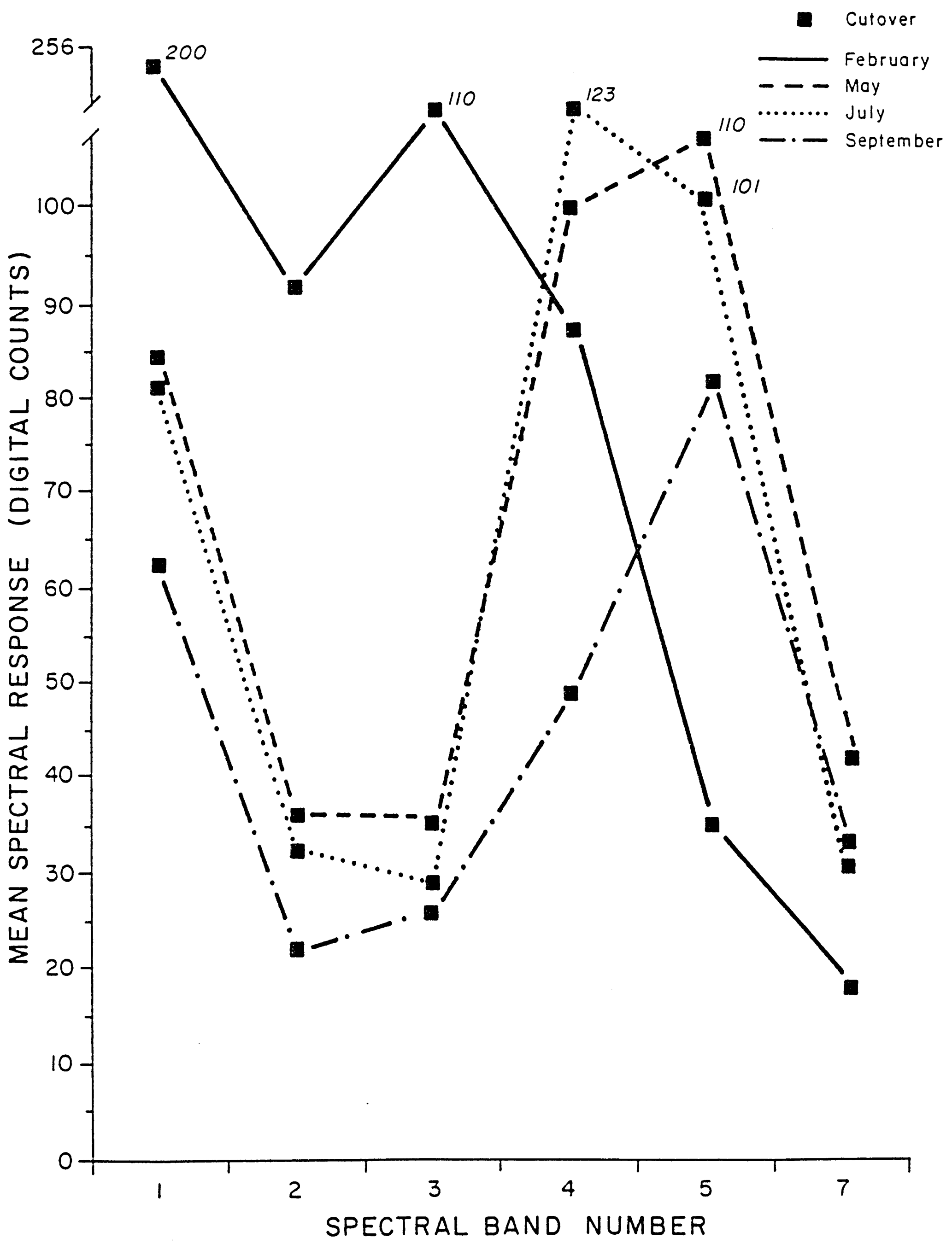

Figure 30. Spectral response patterns of cutover over the six reflective bands of TM data for February 14, May 21, July 8, and September 26, 1985.

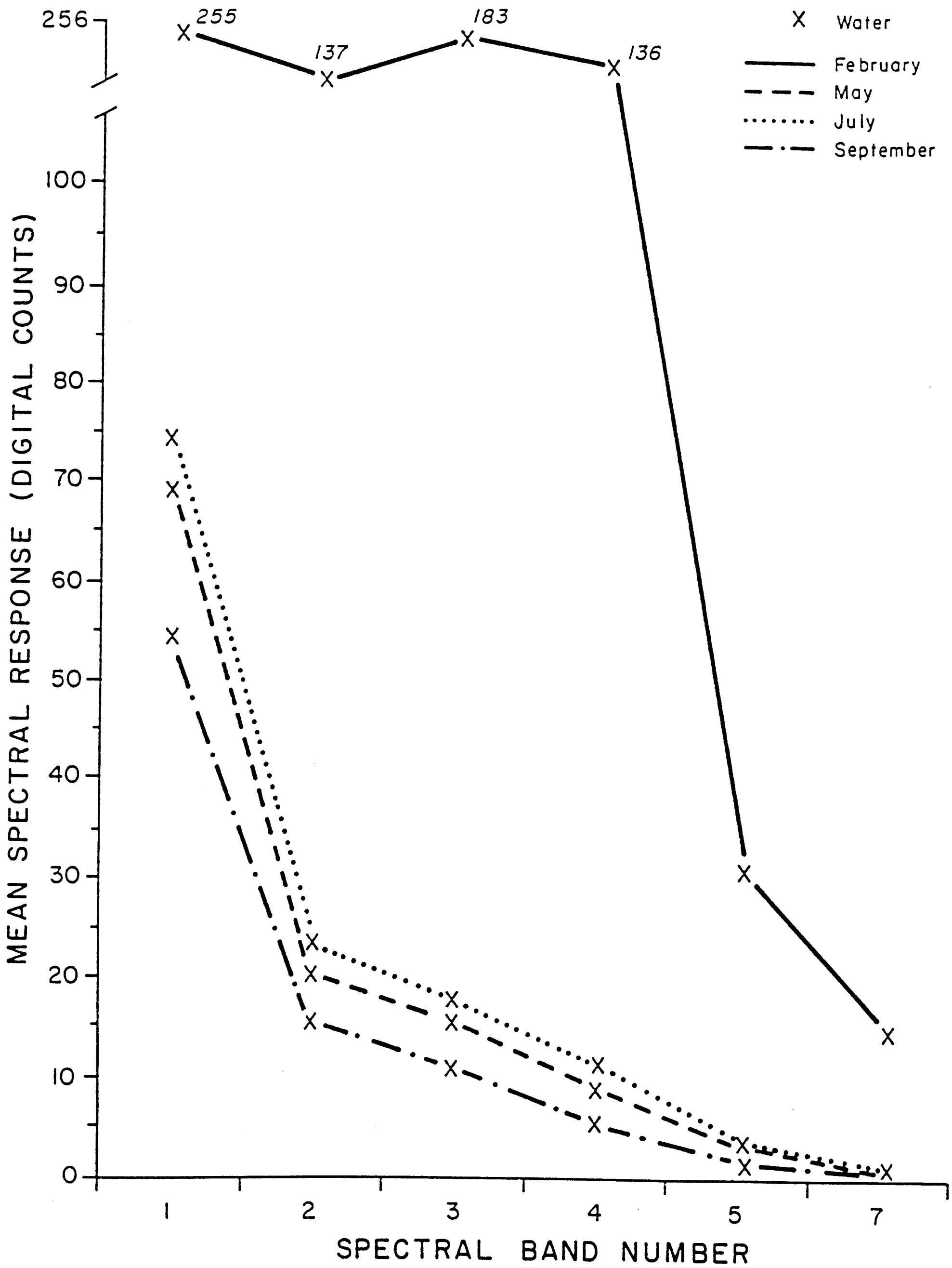

Figure 31. Spectral response patterns of snow/water over the six reflective bands of TM data for February 14, May 21, July 8, and September 26, 1985.

interactions of incident energy and water in the visible wavelengths become more complex. The reflected energy in these wavelengths can be a function of the water surface, suspended material in the water, or materials on the bottom. The chlorophyll concentration in the water also affects the spectral response in the visible wavelengths and is a very useful index of primary productivity and eutrophication (Hoffer, 1978).

Snow, on the other hand, is so reflective in the visible bands that it nearly saturates the detectors on the satellite sensor. In the near infrared bands the reflectance begins to drop until its reflectance is nearly zero in the middle infrared bands (i.e., high water absorbing wavelengths).

Figure 32 overlays the response patterns for the tamarack and black spruce cover types. The black spruce cover type responds very similarly to red pine, except in the first MIR band in May. Red pine has a higher response during that date. Tamarack has a spectral response similar to aspen/birch in the NIR except for May, when Tamarack does not have much leaf area.

The spectral response curves over the various TM bands for the four seasons confirm the usefulness of multitemporal data. The cover types differ in reflectance at various times of year, even though interactions of the multitemporal response with each cover type, and the response of the various wavelengths to changing canopy characteristics is complex.

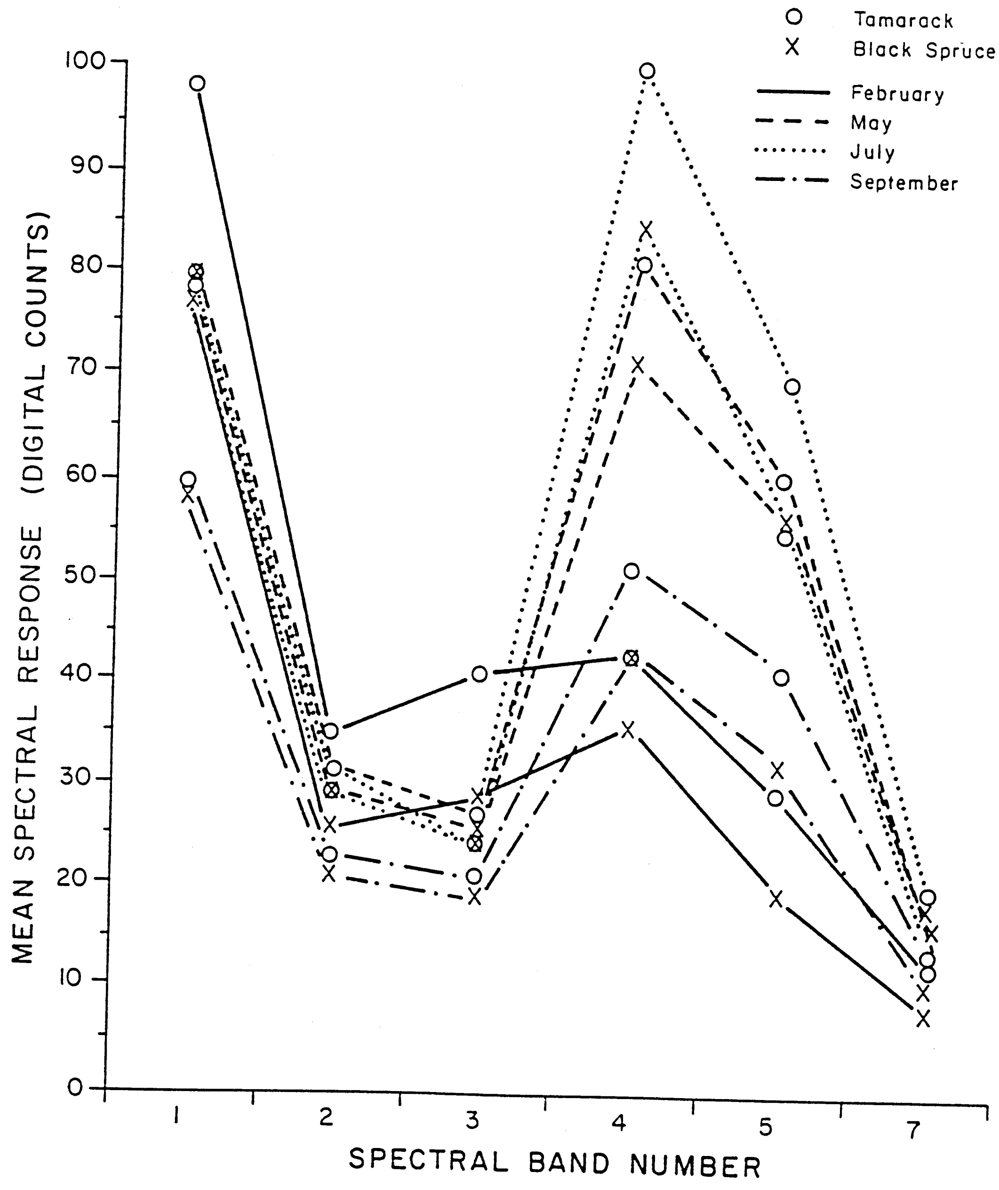

Figure 32. Spectral response patterns of tamarack and black spruce over the six reflective bands of TM data for February 14, May 21, July 8, and September 26, 1985.

4.2.2. Classification Results

The classification results are summarized in Tables 20 and 21, and Figures 33-39. Classification performance is presented for selected band/date combinations using overall accuracy data only, and using the per pixel (no boundary filter) and test field performance measures (4x4 filter). The overall accuracy data were used so that the matrices could be statistically compared. The normalized accuracy results (Appendix 1) have similar trends, yet can be compared only on a relative basis.

Overall classification accuracies indicate that the May and July dates yield the highest results, and are not statistically different. This result was expected since the training data did not show much difference in spectral response for these dates. September and February results are significantly lower with the February date being the lowest. Classification accuracies increased as the individual cover types were aggregated from 14 to 4 classes (Figure 33).

Reasonable classification accuracies were not obtained until the cover types were aggregated into seven Level II and Level III classes. Therefore, I concentrated on results using the following seven classes: upland hardwoods, upland conifers, water, field/grass, marsh/bog and lowland shrubs, lowland conifers, and cutover (various ages). The percent correct using the conventional approach, and the normalized values including errors of omission and commission, for these seven cover types are illustrated in Figure 34 and listed in Tables 20 and 21. Table 20 includes the pixel to pixel comparison of Landsat

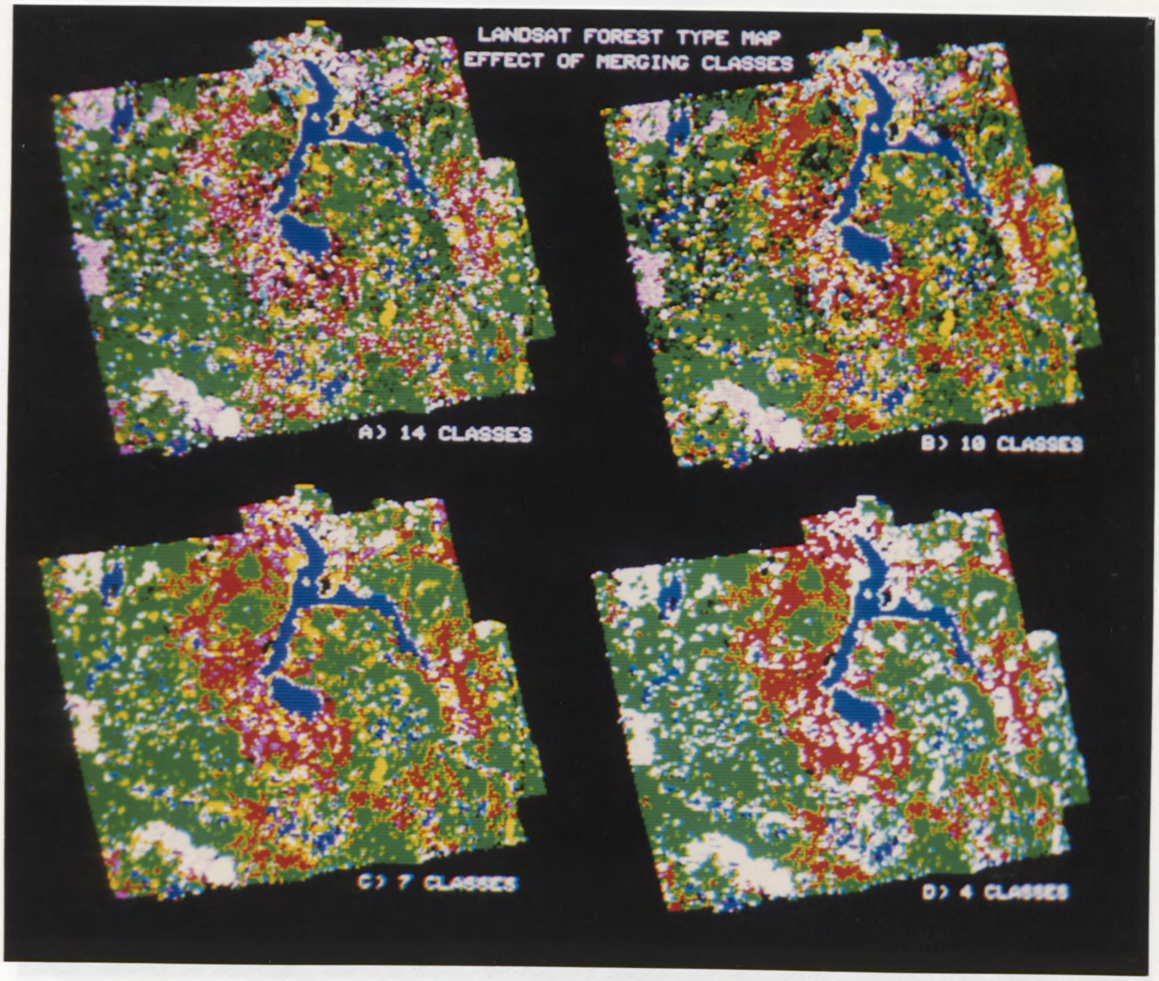

Figure 33. Classification maps with 14, 10, 7, and 4 classes using 30m TM data from May 21, 1985.

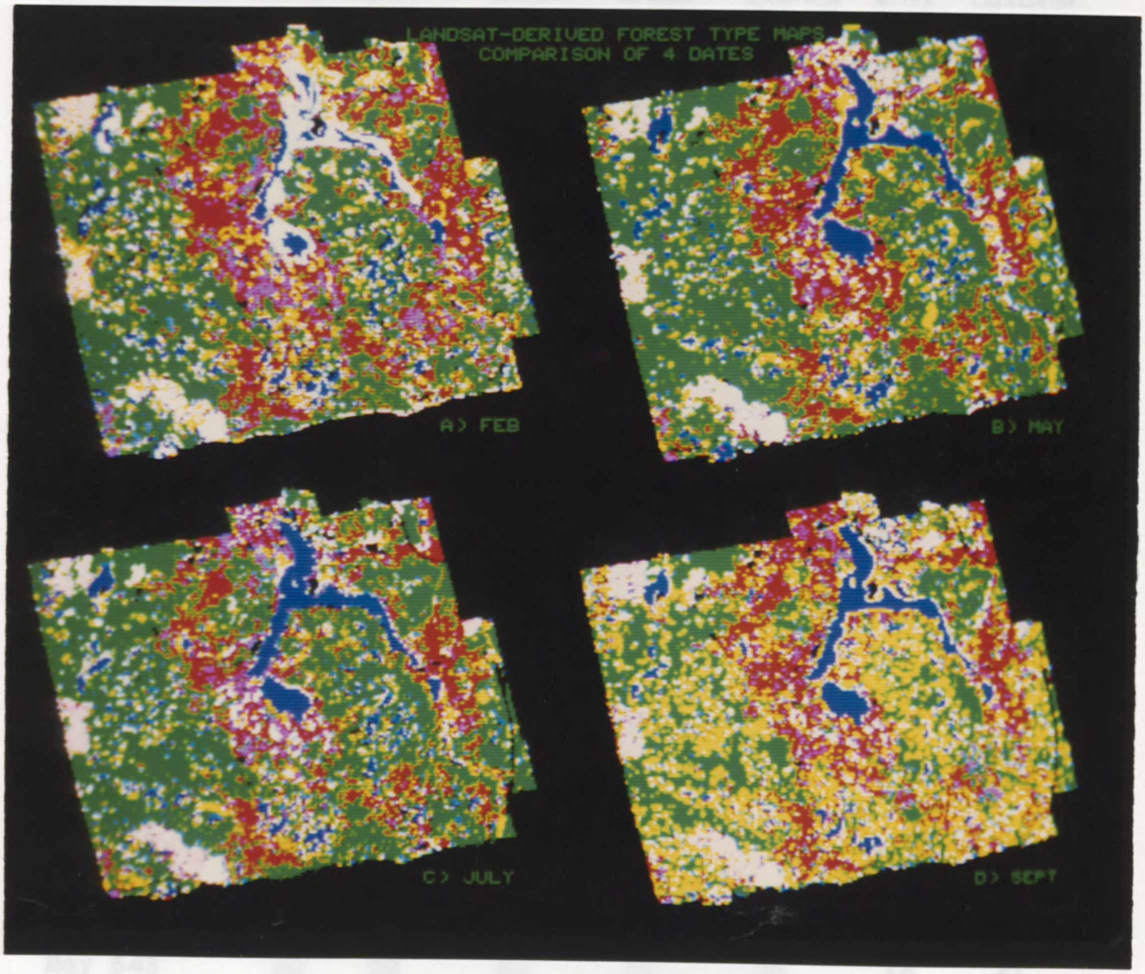

Figure 34. Classification maps using seven resource classes for four dates - May 21, July 8, August 25, and September 26, 1985.

Table 20. Individual class accuracies (%) for seven cover types using the per pixel (no filter) approach. The top number associated with each band/date combination is the conventional percent correct, while the bottom number is the normalized data that includes errors of omission and commission.

	Cover Type						
Date/Band Combination	Upld Hdwd	Upld Cnfr	Water	Fld/ Grass	Mrsh/ L.Shrb	Lwld Cnfr	Cutover
Feb 1-7	62	79	18	34	20	29	43
	55	49	59	61	30	61	53
May 1-7	77	62	45	40	23	24	64
	61	40	79	87	54	68	80
Jul 1-7	78	59	47	42	20	29	52
	59	38	73	84	46	63	76
Sep 1-7	69	58	58	40	20	27	72
	46	38	76	86	40	62	84
Feb 1-6	77	55	21	37	18	22	37
	43	52	51	51	30	54	50
May 1-6	86	50	54	55	18	28	48
	53	52	79	76	50	64	81
Jul 1-6	82	55	64	54	16	25	52
	52	51	77	75	45	63	80
Sep 1-6	73	49	65	40	20	30	72
	41	47	72	77	35	60	80
Feb 5431	67	68	44	41	28	22	39
	52	50	51	54	26	55	54
May 5431	78	59	64	67	29	24	56
	56	47	74	72	40	66	76
Jul 5431	77	58	64	63	23	24	65
	56	47	62	76	38	55	79
Sep 5431	57	57	56	51	40	15	68
	47	39	67	75	34	48	78
Feb 543	70	70	51	40	26	24	40
	53	51	54	55	28	55	58
May 543	80	59	64	61	20	19	51
	58	45	77	66	40	54	71
Jul 543	76	59	60	64	21	19	64
	55	43	63	75	35	52	79
Sep 543	59	58	53	47	36	10	67
	44	35	65	73	35	41	77

Table 20 (cont).

Date/Band Combination	Upld Hdwd	Upld Cnfr	Water	Fld/ Grass	Marsh/ L.Shrb	Lwld Cnfr	Cutover
Feb 541	71	69	40	42	20	24	40
	53	51	47	48	24	56	56
May 541	79	59	61	66	23	29	50
	58	47	78	72	40	63	73
Jul 541	79	54	63	64	21	26	62
	55	44	65	75	36	55	78
Sep 541	57	56	57	50	27	17	63
	44	35	59	76	31	45	76
Band 4	82	56	67	61	31	30	76
(all)	58	50	81	82	47	61	81
Band 45	65	44	33	28	11	71	64
(all)	64	57	90	89	58	36	89

Table 21. Individual class accuracies (%) for seven cover types using the test field (4 x 4 filter) approach. The top number associated with each band/date combination is the conventional percent correct, while the bottom number is the normalized data that includes errors of omission and commission.

	Cover Type						
Date/Band Combination	Upld Hdwd	Upld Cnfr	Water	Fld/ Grass	Mrsh/ L.Shrb	Lwld Cnfr	Cutover
Feb 1-7	76	86	37	76	47	32	50
	69	63	77	77	51	64	60
May 1-7	86	73	75	80	52	40	69
	76	57	90	95	78	81	88
Jul 1-7	87	71	75	81	45	50	56
	76	58	87	94	70	76	87
Sep 1-7	78	71	84	81	87	42	81
	61	53	88	96	61	73	92
Feb 1-6	83	72	39	81	31	23	45
	60	62	69	70	39	58	55
May 1-6	92	66	84	85	42	48	49
	71	70	89	88	73	82	89
Jul 1-6	90	69	84	90	41	55	54
	71	74	90	91	74	84	89
Sep 1-6	81	64	89	86	38	49	81
	55	65	88	94	63	74	90
Feb 5431	78	81	55	82	40	21	46
	65	61	68	68	40	58	61
May 5431	86	74	93	96	60	50	62
	77	68	88	91	69	82	86
Jul 5431	86	71	92	96	53	50	68
	75	67	82	94	70	74	87
Sep 5431	65	73	92	90	60	27	78
	63	55	87	94	59	64	88
Feb 543	79	82	71	80	49	23	46
	67	63	73	72	51	60	65
May 543	87	71	97	88	43	40	55
	75	63	89	85	66	74	83
Jul 543	85	72	94	94	51	42	67
	74	65	85	92	67	74	87
Sep 543	67	72	93	88	52	19	77
	61	49	87	92	58	56	88

Table 21 (cont).

Date/Band Combination	Upld Hdwd	Upld Cnfr	Water	Fld/ Grass	Mrsh/ L.Shrb	Lwld Cnfr	Cutover
				Cover Type			
Feb 541	80	82	47	78	30	22	47
	67	62	60	58	38	60	63
May 541	87	72	96	95	54	56	55
	75	67	91	92	70	81	84
Jul 541	87	67	96	95	47	51	66
	74	65	88	92	66	72	88
Sep 541	66	71	94	91	40	27	72
	60	50	85	92	54	59	86
Band 4 (all)	88	70	91	91	60	44	82
	77	67	85	92	68	76	90
Band 45 (all)	79	62	66	67	34	76	75
	80	70	94	94	82	53	94

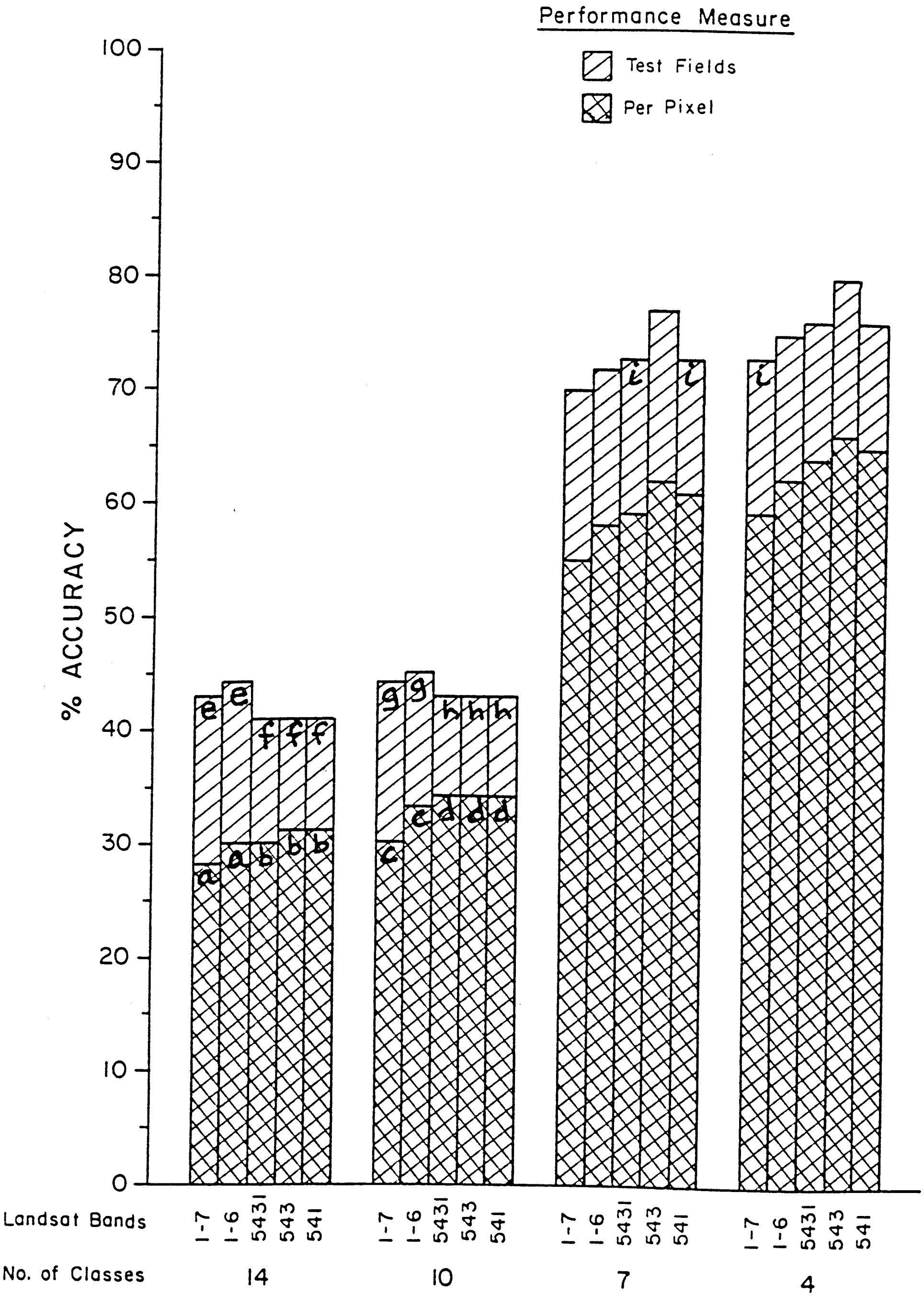

Figure 35. Overall accuracy results for February using various band/date combinations. Results are statistically significant at the α = .05 level unless otherwise indicated with a letter.

classification to the reference data accuracies, while Table 21 lists the test field performance results.

The February data set (Figure 35) for seven classes indicates that TM combination of bands 3,4,and 5 yields the highest accuracies for that date for both pixel by pixel (62%) and test field (77%) results. It is a 7% increase over using all bands (1-7). After comparing class (18% correct for bands 1-7 as compared to 51% for bands 3,4,and 5). The normalized data indicates that both Feb 1-7 and Feb 3,4,5 have the highest overall accuracies, and the individual class results show litte difference between the two data sets with this method. The conventional way to analyze percent correct of individual resource classes may be misleading and lead to gross errors in conclusions and recommendations.

The May data set (Figure 36) for these seven classes illustrates that TM bands 1-6, reflective bands 1,3,4,5; 3,4,5; and 1,4,5 overall accuracy results yield the same results. The per pixel technique had 66% correct while the test field performance was 84% overall accuracy. The normalized data indicates that TM bands 3,4, and 5 has a lower performance than the other band combinations for the May date (76%). Individual class differences are lower for the upland conifer, marsh/lowland shrub, and cutover using bands 3,4,and 5. This would suggest that band 1 is important for discrimination of these cover types.

The July data set (Figure 37) for seven classes shows similar trends to the May date. Statistically the data demonstrate no

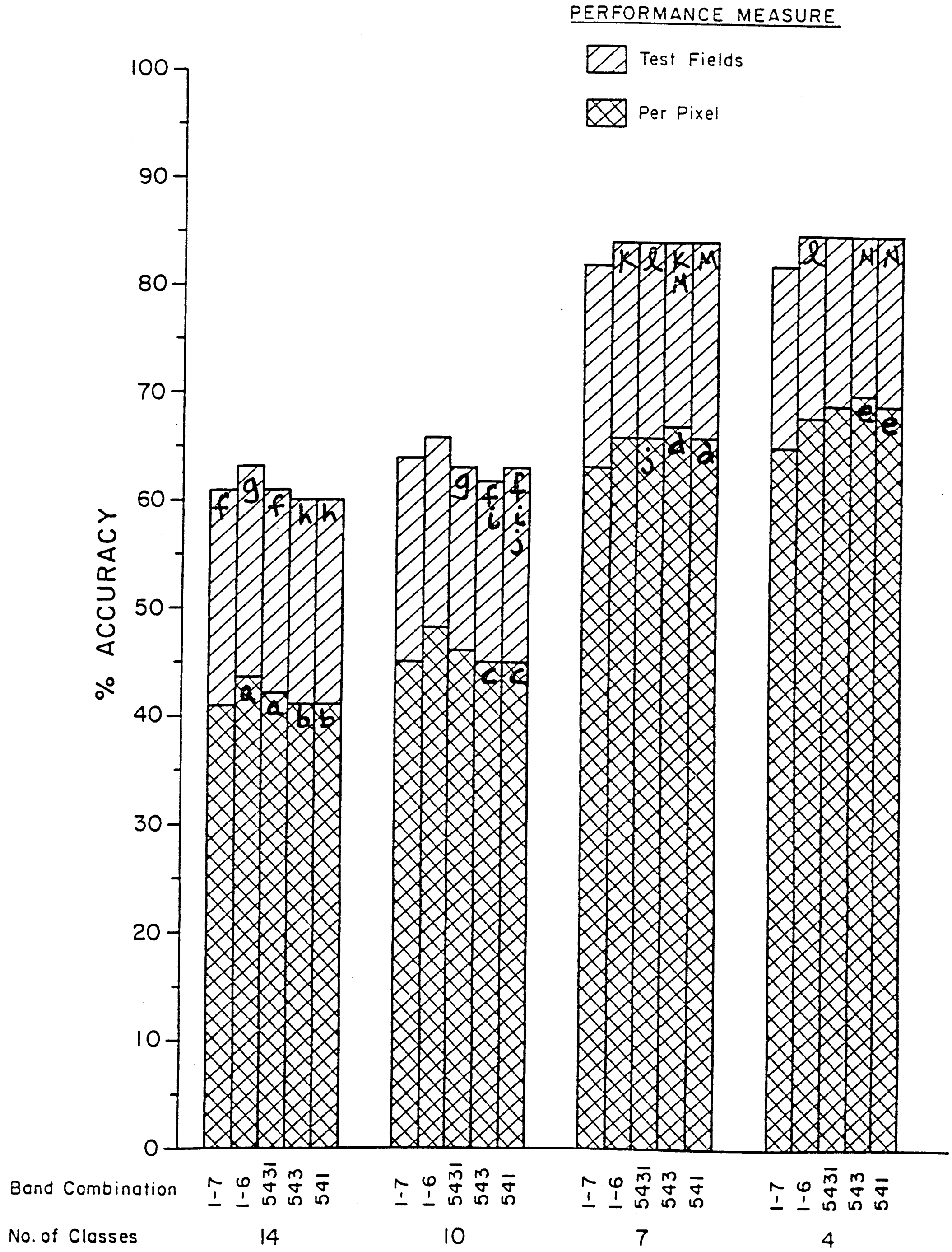

Figure 36. Overall accuracy results for May using various band/date combinations. Results are statistically significant at the α = .05 level unless otherwise indicated with a letter.

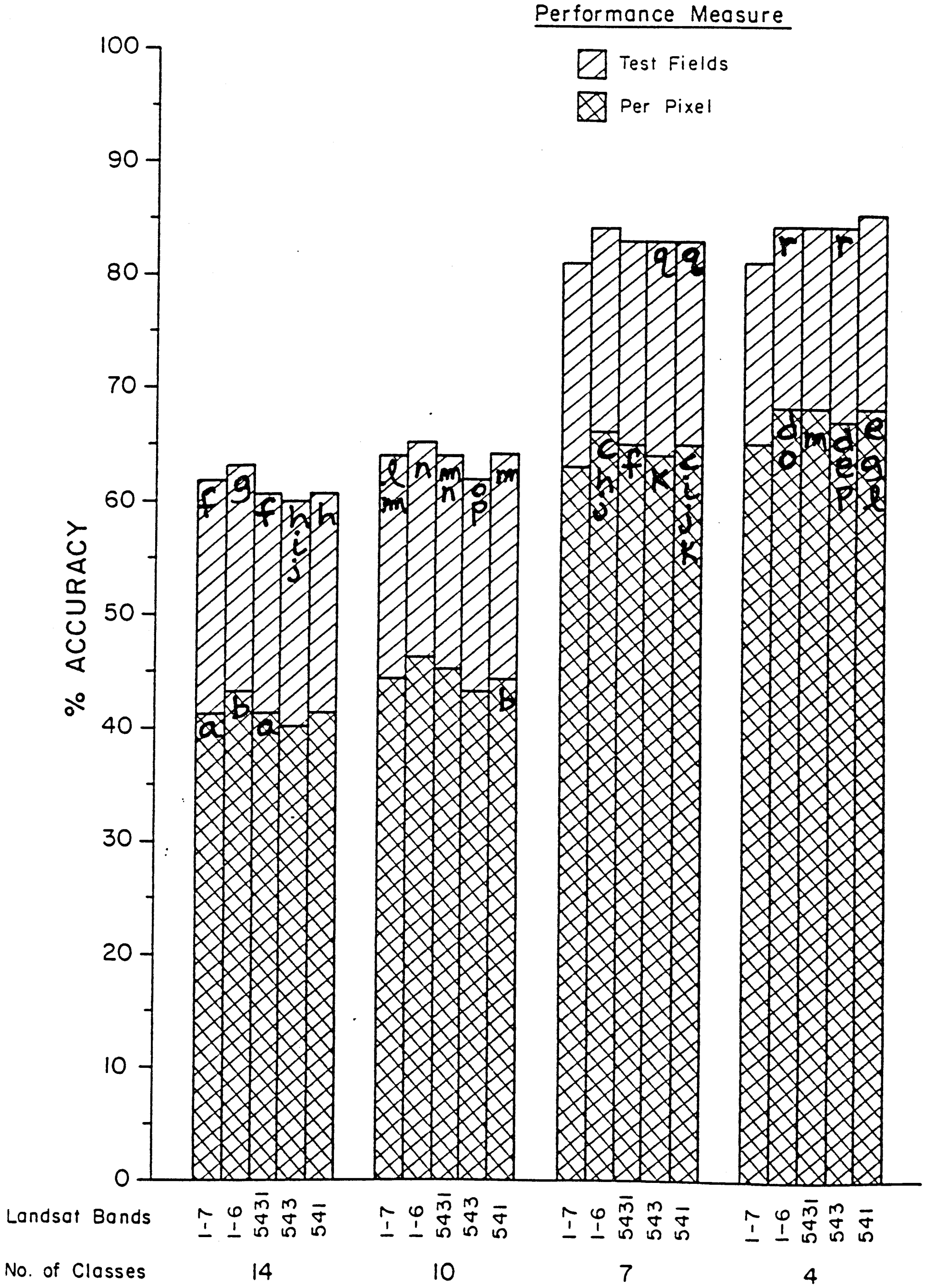

Figure 37. Overall accuracy results for July using various band/date combinations. Results are statistically significant at the α = .05 level unless otherwise indicated with a letter.

individual class accuracies in the Feb 1-7 and Feb 3,4, and 5 data sets. The obvious difference in percent correct is with the water differences in their results. The July date does, however, result in consistently higher accuracies than the May date for the cutover cover type.

The September data set (Figure 38) for seven classes indicates that all seven (1-7) and the six reflective TM bands (1-6) had higher (7-9%) classification accuracies than the remaining combinations. The same trend holds true for the normalized data set for this date. Individual class accuracies were higher for the upland hardwood, lowland conifer and cutover categories using all seven and the six reflective bands suggesting that it may be band 7 that is needed to discriminate between these cover types on this date. Since factors such as moisture content of leaves and shadowing play an important role in the late summer and fall seasons, it is not surprising that an additional middle infrared band increases the classification accuracies.

The classification results from combining the four dates (February May, July, and September) are presented in Figure 39. The overall accuracy results indicate that using band 4 from all four dates gives better results than using a combination of bands 4 and 5. The normalized accuracy results indicate, however, that the opposite is true, and that there are fewer errors of omission and commission using bands 4 and 5 together.

A surprising result is that the combination of the multitemporal

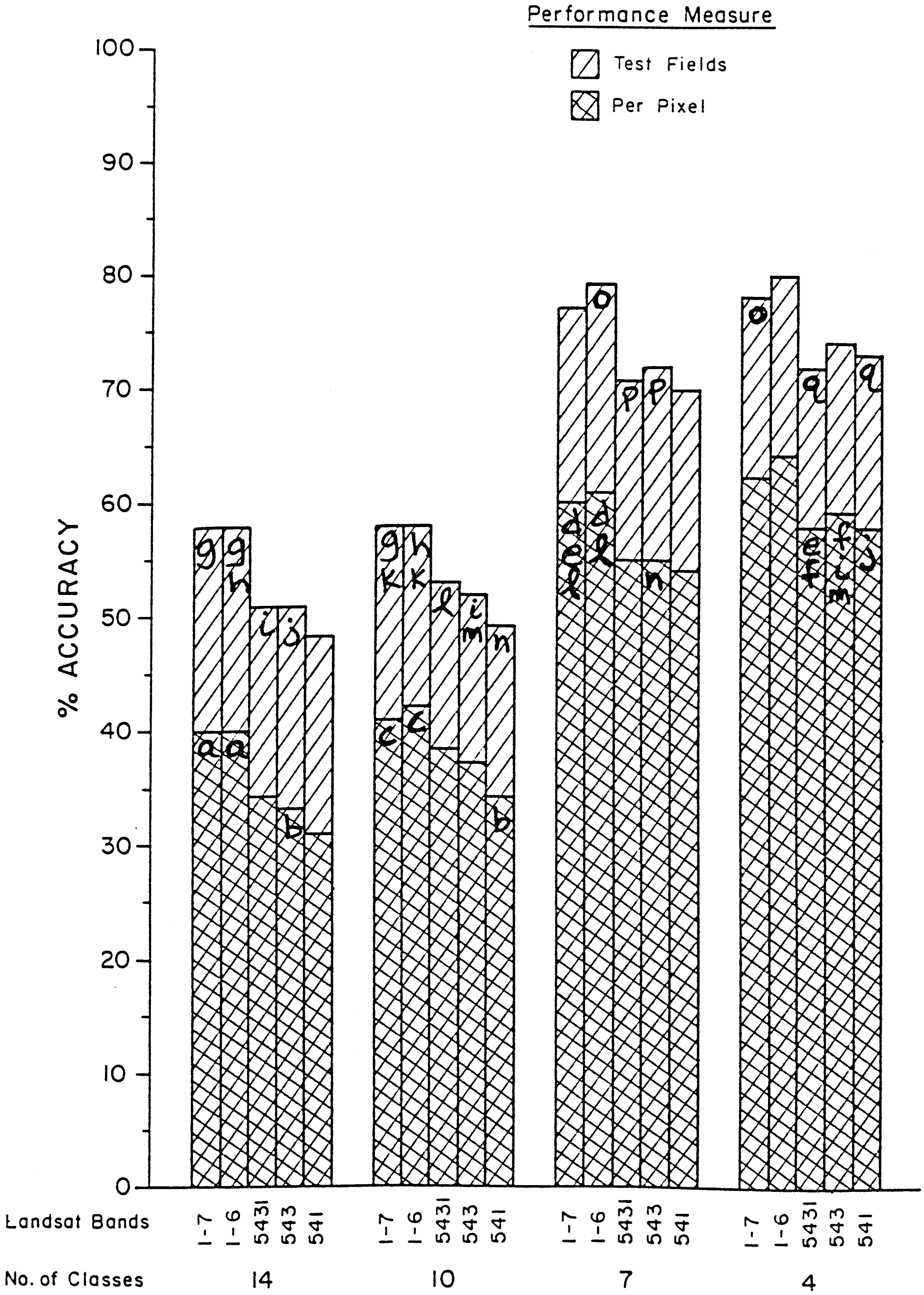

Figure 38. Overall accuracy results for September using various band/date combinations. Results are statistically significant at the α = .05 level unless otherwise indicated with a letter.

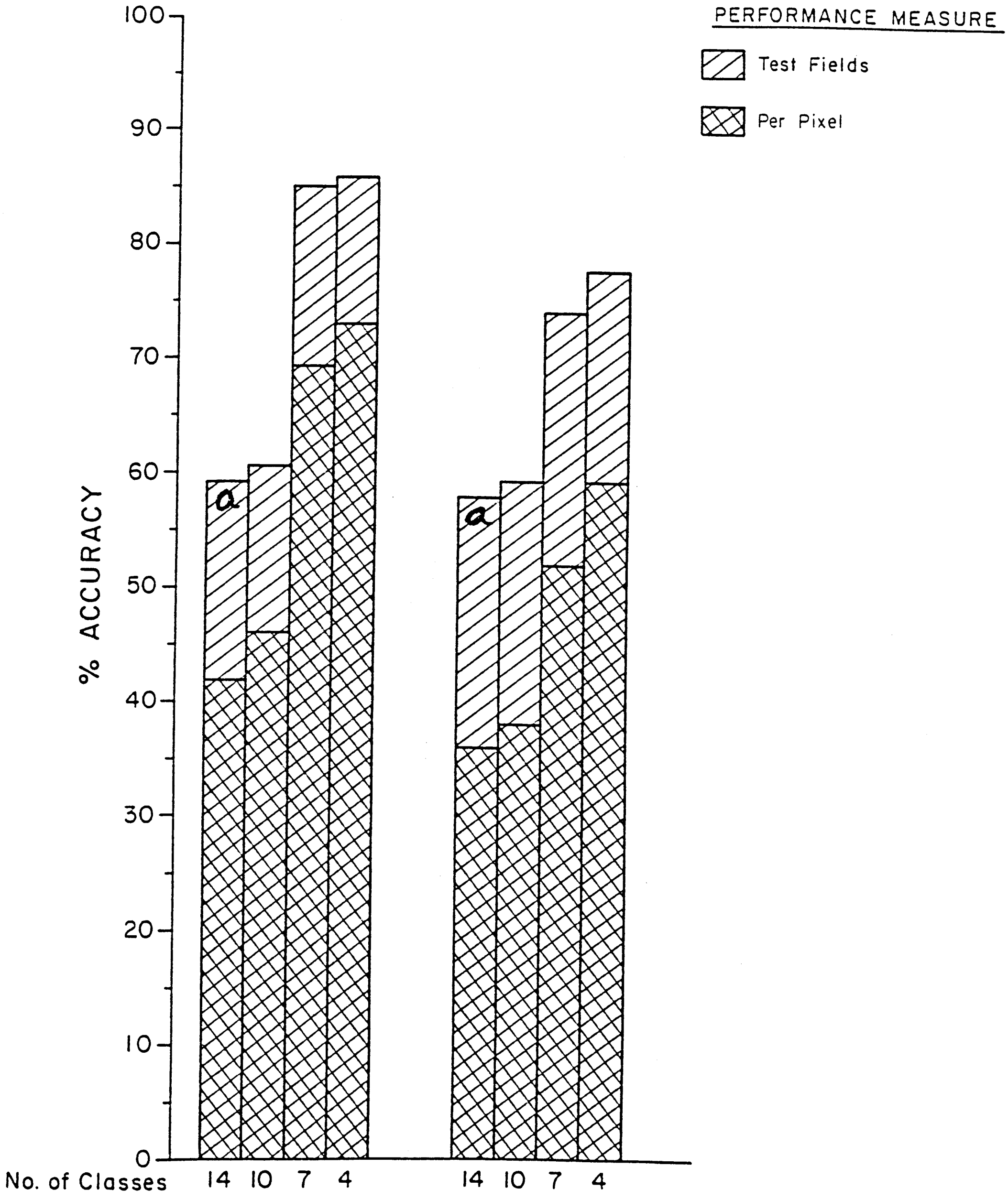

Figure 39. Overall accuracy results for Band 4 and Bands 4 and 5 from each date as a multitemporal data set. Results are statistically significant at the α= .05 level unless otherwise indicated with a letter.

data (Figure 40) did not yield significantly higher overall accuracies than the best single date of either May or July (Figures 36 and 37). However, the normalized accuracies demonstrate for the multitemporal band 4 and 5 combinations were higher for the single dates (10% higher for 14 classes to 4% higher for 4 classes). A possible reason might be that one or more of the spectral bands not included in the multitemporal data was providing a high degree of separability.

The classification accuracy estimates from the band/date combination study illustrate several important points:

(1) The choice of spectral bands is highly date and application dependent. Since I chose the "best" channels based on studies in the literature it is not surprising that the band combinations performed similarly in terms of classification accuracies. The one exception is the September date which exhibited more variability within the band combinations. This early fall date may not yield the highest overall classification accuracies for various cover types, but for basic research it may yield more insight into how fundamental biophysical relationships affect spectral responses.

(2) The results of this study confirm the importance of using at least one band each from the visible, near infrared, and middle infared parts of the spectrum as suggested by other authors from different parts of the country (Teillet et al., 1981; Dean and Hoffer, 1982; Nelson et al., 1984; Benson and DeGloria, 1985). It does not appear that anything is gained statistically by using all seven bands (i.e., the thermal band, band 6, does not play a significant role in this

study). The use of all six reflective bands (TM bands 1,2,3,4,5,7) was important only for the fall date. This may be explained by the sensitivity of TM band 7 to leaf moisture content or shadowing or both. An 8% gain in classification accuracies might be expected by using the six reflective bands for an anaylsis performed in this season.

(3) The classification accuracies are very dependent upon the relative proportions of each category. This problem can be addressed with the use of discrete multivariate statistics and the normalization procedure. For example, the upland hardwood category - which includes aspen, birch, and various northern hardwood species represents approximately 55-60% of the area of Itasca State Park. Therefore, the probability of correctly classifying this cover type is relatively high using conventional techniques (Tables 13 and 14; Upland Hardwood category). The normalization procedure, however, provides a way to eliminate the effect of sample size while incorporating errors of omission and commission into the accuracy assessment. I strongly recommend that anyone presenting remotely-sensed data in the conventional "percent correct" manner also present the discrete multivariate statistics (Congalton et al. 1983: Rosenfield, 1983). The results may otherwise be biased and can be extremely misleading, especially in areas with highly variable vegetation patterns such as those in northern Minnesota.

(4) As Mead and Meyer (1979), Hoffer et. al. (1979), and others have pointed out, the classification results vary with the technique used. For example, it is obvious with the boundary filter experiment

(per pixel versus test field performance) that reported classification accuracies can be increased by eliminating the boundary (mixed) pixels. The test fields demonstrate the potential of the system for identifying certain pure cover types, while the per pixel accuracy measure has a downward bias due to mixed pixels and misregistration problems.

(5) Using the test field results, I was able to obtain classification accuracies that are comparable to results obtained by other researchers conducting satellite classification over forested areas. For the best single dates, either May for July, overall accuracy performance for 14 and 10 Level III categories ranged from 60-66%, while overall accuracies for seven and four Level II classes ranged from 81-85% for a variety of band combinations. Dean and Hoffer (1982), Nelson et al (1984) Benson and DeGloria (1985), Lillesand et al. (1985), and Shen et al. (1985) achieved similar overall classification accuracies for similar numbers and levels of classes. Nelson et al. (1984), in Baxter State Park (Maine), used simulated TM data to classify forest cover types. His classification accuracies peaked at 58% for 13 Level II and Level III classes (e.g., clear cut, old clearcut, hardwood, conifer, bog, water, etc.), and 65% for 10 level II classes. Lillesand et al. (1985) used actual TM data for forest classification research in northern Wisconsin. Using all seven bands, they achieved 98% overall accuracy for Level I non-forest/forest classes; 94% overall accuracy for Level II hardwood/softwood classes; and an average of 69% for nine detailed forest classes (red pine,

lowland conifer, aspen, etc.). Shen et al. (1985), in a study area near Ely, Minnesota using aircraft-acquired TMS reflective bands, obtained an overall accuracy (percent correctly classified in test fields) among coniferous species of 86%, and among deciduous species of 87%. The test field results from this study of Itasca State Park compare favorably with the results from the aforementioned research. The number of correctly classified pixels for the Itasca Park Study peaked at 76% among conifer species, and 86% among deciduous species for May TM bands 1,3,4,5; and 68% and 92%, respectively, among conifers/deciduous species for May using all the reflective bands.

The point of this discussion is that results from the the test field classification accuracies are a measure or indicator of the upper bound on accuracy, and should not be interpreted as indicative of the accuracy that will be obtained when all pixels are considered. On the other hand, the Landsat TM data do yield reasonable results using the pixel by pixel approach. Again, for the best single dates, either May or July, overall accuracy performance for 14 and 10 Level III categories ranged from 41-48%, while overall accuracies for seven and four level II classes ranged from 63-70% for a variety of band combinations. Correctly classified pixels among conifer and deciduous species yielded accuracies of 78% and 63% (65 and 63% for normalized data), respectively, for May bands 5431; while all six reflective bands for May had accuracies of 86% and 53% (61 and 66% for normalized data) for conifer/deciduous classes respectively. Again, it should be noted that there is no a priori or theoretical basis for assuming that mixed, boundary pixels will be correctly classified unless perhaps they are assigned to a mixed pixel class.

A statistical comparison of the overall classification accuracies indicate that the added temporal dimension did not significantly improve the overall performance. A relative comparison of individual class accuracies indicates, however, that this comparison of images taken at different seasons does provide better contrast between certain types of vegetation. For example, using the normalized data, the multitemporal (band 45, all dates) data performed as follows: 8% higher than May bands 1,3,4,5, and 3% higher than May 1-7, for classifying upland hardwoods; 10% better than May bands 1,3,4,5, and 5% higher than May 1-6, for classifying upland conifer; 13% better than May 1,3,4,5, and 8% higher than May 1-6 for classifying the cutover areas.

Mead and Meyer (1977) found the value of using temporally-registered data was difficult to determine and the results were inconclusive. Beaubien (1979) comments that the multitemporal technique is particularly suitable for detailed studies of small areas, but for general vegetation cover mapping of large areas a single date in the middle of the growing season would be of greater use. Merola et al. (1983), using multitemporal Landsat data to detect successional variations in aspen/conifer forest, increased overall accuracies by only 4% by combining several dates. However, several individual classes increased by 12% or more. There is still much work to be done in this significant area of research. The stacked vector approach may not be the appropriate method for analyzing multitemporal data.

4.4. Greenness-Temporal Profile Study

The primary objective of this study was to investigate the use of the Greenness-Brightness transformation (Crist and Cicone, 1984a) and the temporal profile model (Badhwar et al., 1982) for forest cover type classification using Thematic Mapper data. Although these approaches have improved crop identification, and are considered to be significant advancements for agricultural remote sensing, no studies investigating their possibilities in forest applications have been published.

4.4.1. Spectral Response Analysis

Greenness is a weighted difference between the NIR and visible bands, and is strongly related to the amount of green vegetation in the scene. Numerous studies with agronomic crops have shown moderate to high correlations of measures of amount of green vegetation, such as percent canopy closure, leaf area index (LAI), and fresh biomass to greenness (Bauer et al., 1986).

Mean spectral responses for greenness as a function of the day of year are shown in Figure 40. The data were taken from aggregated training samples for four cover types (aspen/birch, red pine, cutover, and water).

Aspen appears to reach peak greenness near the end of May, then remain fairly constant for the remainder of the growing season. It

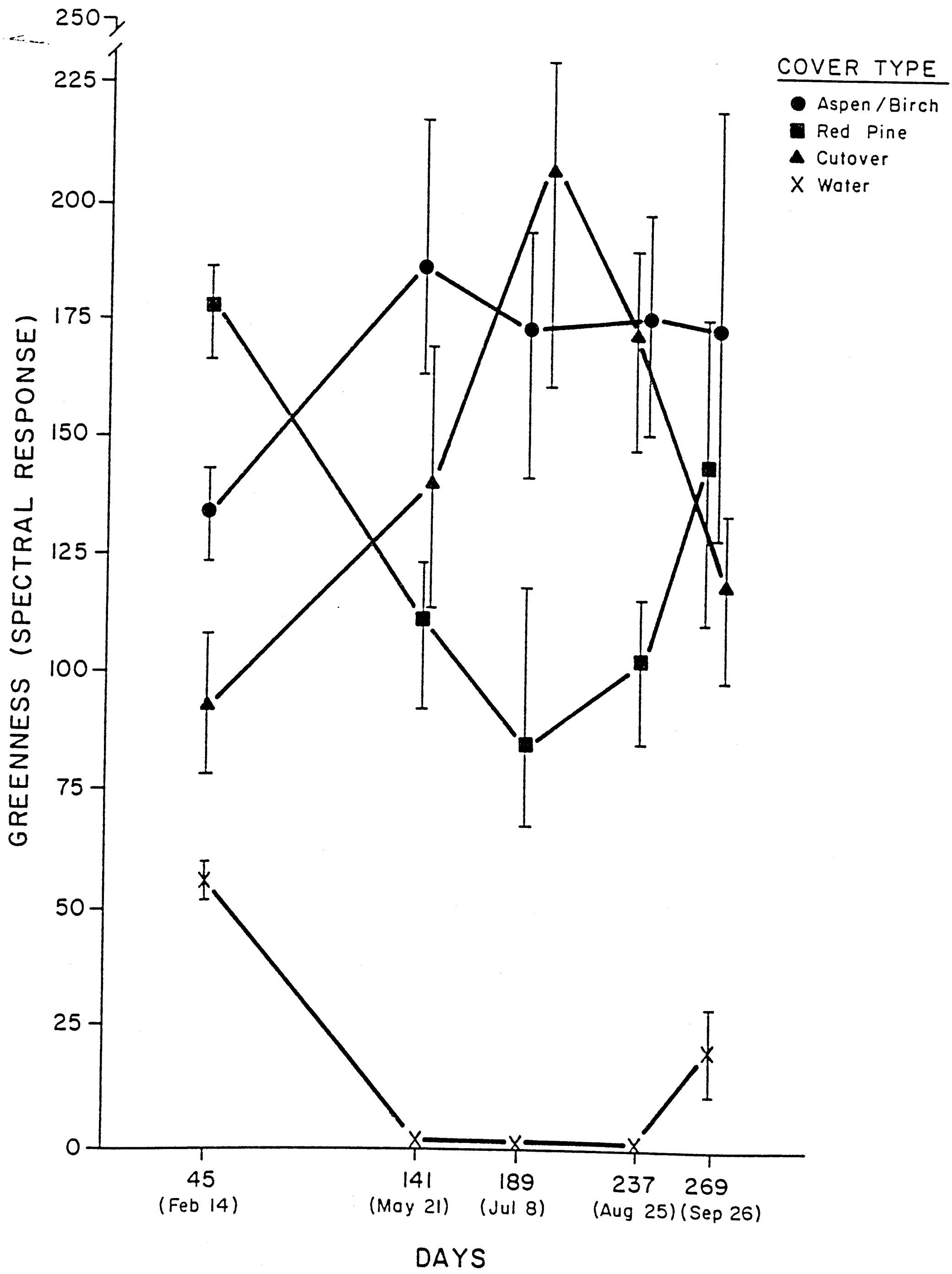

Figure 40. Spectral response for greenness over time for four cover types - aspen, red pine, cutover, and water.

would seem reasonable to speculate that this peak greenness corresponds with increasing canopy closure and LAI of this cover type. Observations by Ahlgren (1957) and Pollard (1970) indicate that it takes aspen approximately three weeks from bud break to reach 88 percent of maximum LAI. Badhwar et al. (1986), studying the relationship between TM band reflectance and LAI for aspen near Ely, Minnesota, determined that the band 4 (NIR) and band 3 (red) ratio was sensitive to both overstory and understory canopy. If there was little understory LAI (as would be the case in the early spring) then band 4 would increase with increasing overstory LAI, while band 3 would decrease. So there is a fair amount of sensitivity in this greenness value for the aspen overstory early in the season when no understory is present. However, as understory LAI increases the band 4/3 ratio loses its sensitivity to the overstory LAI.

The cutover cover type appears to reach peak greenness on the July date. The cutover areas have a mixture of herbaceous species, shrubs and young saplings which will cause high variation in the spectral response. Many of the species that make up this cover type do not begin canopy development until late spring. Again, it would seem reasonable to speculate that increased canopy closure, increased LAI of the herbaceous and woody species, and increased biomass of the herbaceous species for this cover type are correlated with this peak in July. Harlan et al. (1979) and several others have demonstrated a linear relationship of herbaceous green biomass and the Landsat band 4/3 ratio.

The red pine cover type remains fairly constant in greenness response throughout the growing season, and reaches a slight peak in the early Fall (September date). The peak in greenness for red pine, however, is in February. I hesitate to hypothesize why greenness is behaving the way it is for this cover type during the winter season. Perhaps the explanation lies in the background influences.

I am reluctant to make specific statements concerning the relationship of the greenness response and the various canopy characteristics. Since I did not specifically isolate the various biophysical characteristics (e.g., LAI, canopy closure, biomass), I must exercise caution in my speculations until more complete estimates of the canopy characteristics are obtained.

Greenness response of the water (and snow) category was illustrated with the vegetation cover types as a control. The spectral response behavior of clear water in the visible and infrared bands is fairly predictable. Since the water category behaved as predicted, I assumed the general trends of greenness response for the other categories are correct.

Figure 40 illustrates that these four cover types can be separated on the basis of their greenness spectral response. Based on these training data it appears that these four cover types can be separated on the February and May dates. However, I did not use the February date in the final classification. The aspen/birch and cutover cover types have similar greenness response on the summer dates, although the cutover cover type has a much higher mean response during July. All of the vegetation cover types respond similarly in September, with the aspen/birch being quite variable. This information can be used to help explain errors in classification using greenness and the temporal profile parameters.

4.4.2. <u>Classification Results</u>

Four dates (May, July, August, September, 1985) of greenness response were combined and analyzed as one image. The greenness responses from these same dates were modeled over time using the temporal profile model. The parameters (i.e., images) resulting from the profile model (Figure 8) were analyzed to determine the applicability of this model for classifying forest cover types. The six parameters from the model (alpha, beta, Gmax, time of peak greenness, sigma, and Gmax - Go) were analyzed as a six band set; and a subset of these (Gmax, time of peak greenness, and sigma) was analyzed separately as a three-variable data set. The classification results of greenness response from the four dates were compared to the results from the temporal profile model, and from the single date/band combination study.

Figures 41 and 42 illustrate and Table 22 summarizes the results from the greenness and temporal profile classifications. Greenness classification results are superior to the temporal profile model approach. Within the temporal profile model results, the classification accuracies of the six parameters were higher than with three.

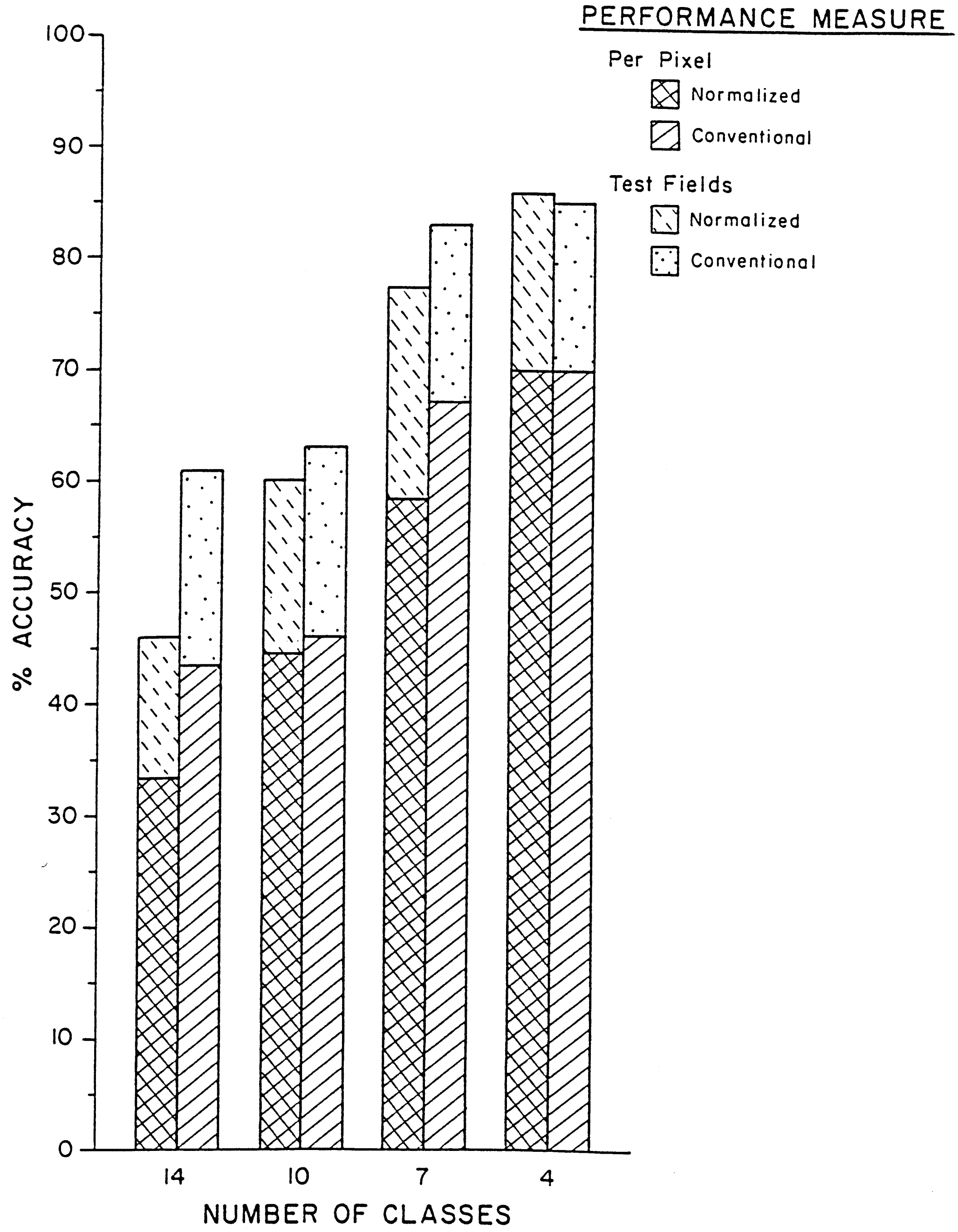

Figure 41. Overall classification results from the greenness response for four dates (May, July, August, September, 1985). Using the stacked vector approach. Results are statistically significant at the α = .05 level unless otherwise indicated with a letter.

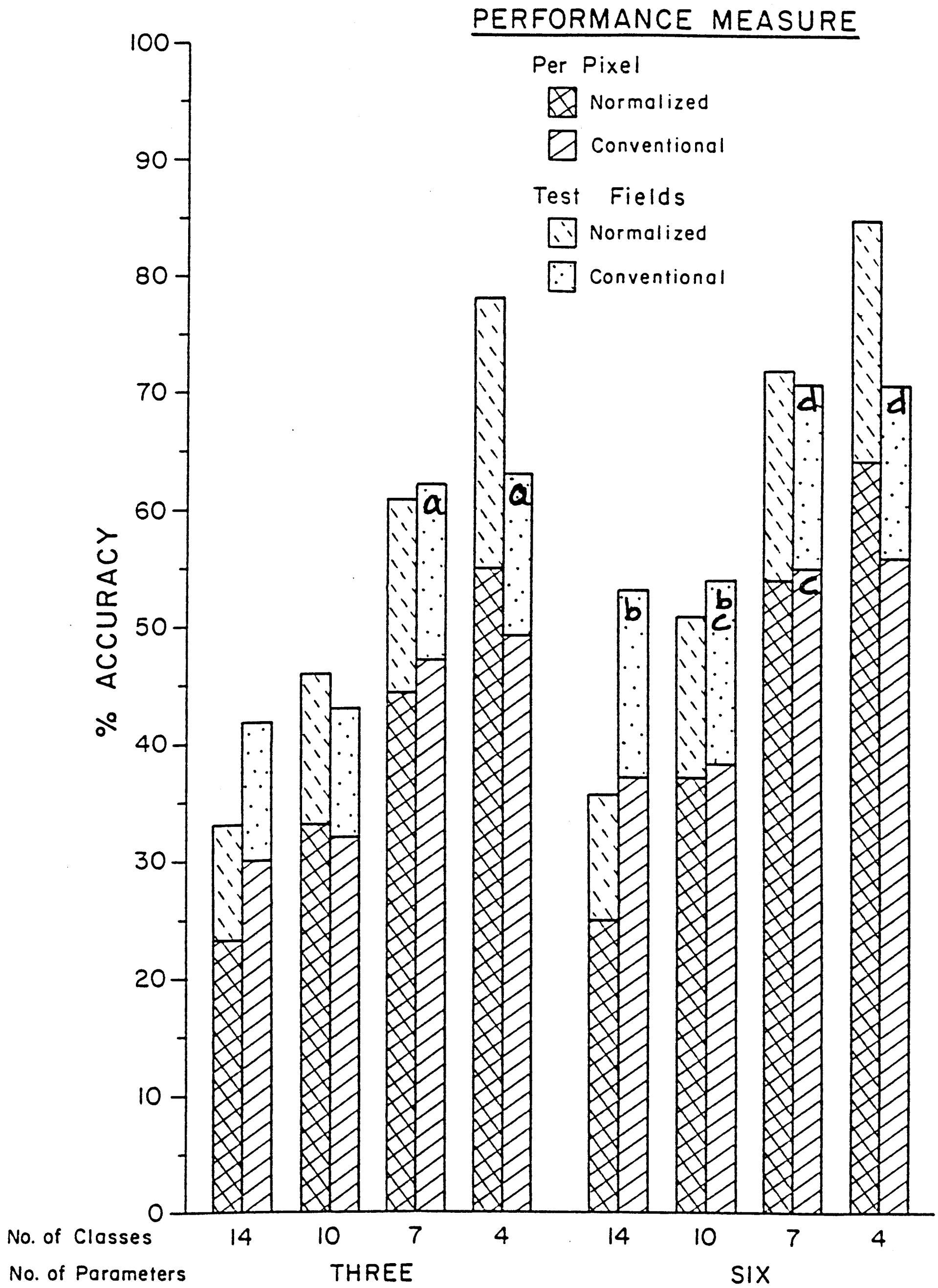

Figure 42. Overall classification results from the temporal profile model using six parameters (alpha, beta, Gmax, tp, sigma, and Gmax-Go), and three parameters (Gmax, tp, and sigma).

Table 22. Individual class accuracies for seven cover types using the per pixel (no filter) and test field (4x4) approach for greenness and the temporal profile model (Profile), with three and six parameters. The top number associated with either greenness or profile is the conventional percent correct, while the bottom number is the normalized data that includes errors of omission and commission.

	Cover Type						
Analysis Method	Upld Hdwd	Upld Cnfr	Water	Fld/ Grass	Mrsh L.Shrb	Lwld Cnfr	Cutover
			Per Pixel				
Greenness	77	57	69	47	30	17	66
	56	44	82	69	40	48	68
Profile							
Three	51	37	93	28	1	14	28
	48	39	62	63	22	33	43
Six	63	46	92	23	4	12	21
	51	50	64	71	33	45	63
			Test Fields				
Greenness	84	71	97	85	70	26	75
	74	60	94	90	74	68	81
Profile							
Three	60	51	100	40	5	20	31
	69	50	88	84	39	43	57
Six	72	60	100	36	4	21	25
	72	69	91	87	57	53	76

Overall accuracy results indicate that, for seven classes, results with greenness are 12% higher than those from the temporal profile with six parameters. This difference decreases slightly with normalized results although accuracies of greenness classification remain higher. When compared to the overall accuracies of the best single date, greenness has similar results to May and July. The best single dates had slightly higher normalized values.

The greenness transformation and the temporal profile model were used in this study to determine the applicability of these techniques for forest cover type classification. Although these techniques yield significantly higher accuracies when used to analyze agricultural crops, they do not appear to have the same response in highly variable vegetation types such as those in Itasca State Park. Although the initial results were disappointing, I feel these approaches are still new and not yet fully understood.

The temporal profile technique, for example, uses a regression model which follows the general trend of the sigmoid growth curve. If the greenness response of the cover type is flat or differs from the sigmoid growth curve, however, the model cannot be fit and those values are assigned a zero value. This is what we believe happens to many of the water and conifer cover types (Figure 40). A suggestion would be to first stratify the conifer and deciduous cover types, then fit the temporal profile model separately to the stratified data. Also, nonlinear models would probably better fit the data.

The point is that these techniques have very appealing qualities. They emphasize and are sensitive to biophysical properties of the scene. The temporal profile model needs to be adjusted, however, to fit the greenness response of various forest types rather than those of agricultural crops. This is an area of research that has much potential.

5. CONCLUSIONS AND RECOMMENDATIONS

This study was conducted to evaluate the newest Landsat satellite sensor, the Thematic Mapper, for its usefulness in classifying forest cover types in Itasca State Park. Specifically the objectives were: (1) to determine if the Thematic Mapper is in fact superior to the older sensor, the Multispectral Scanner, for forest cover type classification; and if the Thematic Mapper data does yield higher accuracies, is spatial or spectral resolution responsible; (2) to determine which Thematic Mapper band and date combinations (from four seasons, February, May, July, September, 1985) yielded the highest classification accuracies; and finally, (3) to evaluate the use of several techniques that have proven to be very successful for classifying agricultural crops, the Greenness-Brightness transformation and the Temporal Profile model, to determine if a similar response is possible for classifying forest types.

The following summarize the results of this study:

(1) The overall results of forest classification using the Thematic Mapper sensor were significantly more accurate than those from the Multispectral Scanner. The increases in classification accuracy are more closely related to the higher spectral resolution of the Thematic Mapper than to its greater spatial resolution. However, the spatial resolution of TM images is of excellent quality, and could be very useful for direct image interpretation.

(2) The highly variable and mixed vegetation of north-central Minnesota necessitates the aggregation of most Level III cover types

into Level II (or a mix of Level II and Level III) cover types to achieve classification accuracies that can be used for county or statewide inventories.

(3) Landsat scenes of complex vegetation types such as those of Minnesota may contain from 35-50% boundary pixels. These boundary or mixed pixels will have an increased probability of being misclassified. Boundary filters can be used to eliminate part of this mixed pixel problem. A boundary filter that eliminates the effects of both misregistration and of some of the natural boundaries is recommended if Landsat classified data (i.e., continuous data) is to be directly compared to reference data (i.e., discrete data).

(4) Boundary filters can be used to such an extreme that all that is left is a pure, homogeneous, cover type. Classification accuracies based on these pure, homogeneous areas (e.g., test fields) can be biased and misleading if the results are implied to represent the entire study area.

(5) Analysis of Landsat Thematic Mapper data taken from four seasons over Itasca State Park indicated that the best dates for overall classification accuracies are late May and early July.

(6) This study agrees with others using Thematic Mapper Simulator data that at least one band each from the visible, near infrared, and middle infrared portions of the spectrum is recommended for best overall classification of vegetation. Using all six reflective bands is recommended if a fall date is being classified, or may be needed to

significantly increase the accuracy of recognition for an individual cover type.

(7) Insufficient analyses were conducted to make any conclusive remarks concerning the contribution of the thermal infrared band.

(8) Analysis of multitemporal data (combining band 4, and band 4 and 5 from four dates) generally did not significantly increase classification accuracies of cover types in Itasca State Park over the best single dates. If the accuracies were increased using the multitemporal data set it was only a slight improvement, insufficient to justify the cost of four dates for an inventory over a large area. New approaches need to be developed for analysis of multitemporal data other than the conventional stacked vector technique.

(9) Two techniques that have proven successful for improving classifications of agricultural crops were evaluated for their effectiveness in forest situations - the greenness transformation and the temporal profile model. Classification results of data using the stacked vector greenness were higher than for the temporal profile model; however, the results using the greenness transformation, in general, were not statistically different from the best single date analysis.

(10) Although the greenness transformation and the temporal profile model did not yield higher classification accuracies than did the conventional approaches, both have appealing qualities that deserve further research. Biophysical (e.g., LAI, canopy closure, biomass) properties are emphasized, yet the interaction of these properties and

their spectral response over time is not well understood. The changes in biophysical characteristics and greenness response over a season in a forest environment are obviously not the same as those for agricultural scenes. The temporal profile model will, therefore, have to be adjusted to follow the spectral responses of forest vegetation. The responses will depend upon the major species and cover type composition. The use of the greenness transformation and temporal profile model in forest environments needs more research in model development and a basic understanding of interactions between spectral response and canopy characteristics.

(11) This study was conducted on the cover types within Itasca State Park. Much of the analysis is similar to a fixed effects model in an experimental design. Extrapolations to other areas in northern Minnesota must, therefore, be used with caution. It is recommended that the best techniques found in this study be tested on additional sites.

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